STUDIES ON JAPANESE CONCERT TICKET RESALE AUCTIONS

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ABSTRACT

The way concert tickets for JPOP (Japanese pop) artists are typically sold in the primary market causes concerts tickets to be sold without seating quality information for some periods of time in the secondary markets which is dominated by Yahoo! Auction. There are two main aims of this research. First, we investigated how auction outcomes were determined in this particular market. Second, we studied how a proportion of buyers in this market create 'missed opportunities' by not placing a bid on the auction with the lowest standing bid for similar and highly substitutable goods. To do this, we generated a unique dataset of online auctions for concert tickets in Japan and used the data to investigate several important features of the secondary market.

In Chapter 3 we examined the determinants of auctions' outcomes: success and closing price in this unique environment. In particular, we investigated the impact of certainty in seat quality on auctions` success and closing price. The econometrics estimation results showed that tickets that were auctioned with certain seat quality have higher probability of success; this result was robust to changes in econometrics methods, control variables, and samples. The effect of seat certainty on auctions' closing price was less clear, it showed positive and significant impact when we estimated the model using Fixed Effect OLS but we found no impact when we used Truncated Regression. However, we found that for top traded concerts, tickets with certain seat quality tends to generate higher closing price taking all other control variables constant irrespective of econometrics method being used. In addition, we found similar result when we control heterogeneity by adding cluster averages in the regression.

Relaxing the typical assumption in auction theory that one auction is independent of another, in Chapter 4, we examined whether bidders generate 'missed opportunities' in their bidding strategy by not bidding on the auction with the lowest standing bid. The data showed that bidders did not always bid on the lowest standing bid in competing auctions for similar and highly substitutable goods. When goods were homogenous and when sellers were identical within Groups of Competing Auctions (GCA), missed opportunities were lower but still substantial.

Although the size of missed opportunities (errors) was not large for the majority of the GCAs, errors were higher than tickets' face value in 20%to 40% of the GCAs. Some of those errors were very large. Errors were smaller when goods were more homogenous (uncertain tickets) and when sellers were identical within GCA. Nevertheless, in some cases, rate of missed opportunities and size of errors were very high even when goods ere similar and sellers ere identical e.g. AKB48.

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CHAPTER 1 INTRODUCTION

1.1 Introduction

Japan is the second largest market for live music.[1] Based on annual reports produced by All Japan Concert and Live Event Promoters Conference (ACPC)[2], the total sales of live music in Japan in 2013 reached ￥231 billion (approximately $2.3 billion) annually. Many tickets bought in the primary market are later resold in the secondary market. There is no official study conducted to gauge the size of Japan's resale ticket market. However, its resale market has also been thriving as showed by the growth in both the total value of the tickets auctioned and the number of successful auctions in Yahoo Japan Auction[3], which is the major auction site for concert tickets. In this research we construct a unique dataset of online auctions for concert tickets in Japan and use the data to investigate several important features of the secondary market. In particular, we focus on two main issues. First, we investigate how auctions' success and closing price were determined in this particular market. Second, we learn how a proportion of buyers in this market create 'missed opportunities' by not placing a bid on the auction with the lowest standing bid given although the goods that were auctioned were similar in quality and highly substitutable.

Although there are numerous prior studies on auction outcomes, this study is unique since the Japanese ticket market is different from North American market and many other countries in several ways. The most relevant difference that inspired this

[1] There are no official organizations reporting on live music statistics in the similar manner as IFPI reports for recorded market, Live Nation Japan Notice of Establishment (2012) mentioned Japan as the second biggest live music market in the world.

[2] ACPC is an association of Japan live music promoters. Not all concert promoters are members of ACPC, however all major promoters are members of ACPC. They conducted research and published data on live music. They also maintain, manage, and conserve of the intellectual property rights relating to Live Entertainment Business.

[3] The total value of tickets auctioned in Yahoo Japan Auction increased from ￥4,7 billion in 2011 to ￥5,3 billion in 2014 while successful transactions increased from 299.373 to 301.539 transactions for the same period.

study is that in Japan tickets are sold without the seating information most of the time. This is unlike what usually practiced in other countries where fans can select the seat or at least the area the seat is located when they buy their tickets.

In Japan, tickets are usually sold in advance about two months before the event on average or earlier and buyers generally receive the tickets one or two weeks before the event. Only at that time buyers learn the seat quality. Nevertheless, although buyers for Japanese concert tickets do not know about the seat quality printed in the tickets they buy as they do not receive their tickets until near the concert date, they usually learn whether they win the ticket or not prior to the announcement of the seating arrangement. As a result, some sellers and buyers of the tickets in the secondary market engage in trades while having no information about the seating quality.

This lack of information is exacerbated by the fact that tickets are rarely price discriminated in Japan. Generally, price discrimination is done based on how the venue is scaled into different seating areas. That way, buyers can gauge the general quality of the seat from the price of the tickets. In contrast, often, Japanese fans cannot discern where their seat going to be in any way when they buy their tickets. Lastly, in most concerts in Japan, tickets are sold through lottery (rationed) in advanced through several phases instead of through more common first come first served basis.

So, buying concert tickets for popular Japanese Pop Group (JPOP) for foreigners in Japan is probably a novelty. Instead of watching our computer screen intently for the selling time to start then punching the buying button as fast as we can to get the best seat available given our budget like we usually do, we can leisurely apply for the tickets during application period that lasts for weeks. However, not only that we will not be able to know whether we get the ticket until later time because it is usually determined

by lottery but we can't choose your seat location most of the times either. Although this market features probably affect economic agents' behavior as well as economic outcomes, to the best of our knowledge, this particular case study of product quality uncertainty has never been explored before.

While Japan concert ticket primary market data is not publicly available, concert ticket secondary market data can be extracted from Yahoo Japan Auction, which is the biggest online auction platform in Japan. There have been numerous research conducted on auctions. Some of them also focused on the effect of quality certainty on auctions' outcomes.[4] However instead of product quality certainty, they focused on sellers' quality certainty or credibility.

Moreover, most of the empirical research on auctions use data collected from eBay, which has different institutional rules from Yahoo Japan Auction. They have different ending rules and different mechanism regarding Buy It Now option. Yahoo Japan Auction allows sellers to extend the auction's ending time for 5 minutes if at least one bid is submitted in the final 5 minutes before the auction ends. Therefore it is harder to snipe here compared to on eBay.[5] Also, Buy It Now (BIN) does not vanish although the auction has received a bid as long as the bids are not equal or higher than the Buy It Now (BIN) price.

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[4] Some of notable studies that explored the effect of sellers' uncertainty, which is reflected by sellers' feedback included Menik and Alm (2002), Livingston (2005), Lucking Reily et.al (2007), and Liu et al. (2013) who employed Japan and Taiwan data in their study.

[5] Sniping is a phenomenon where bidders submitted very late in an auction (late minute bidding) near the time the auction ends or at the time it ends. This is practiced likely in order to exceed the current highest bid as late as possible and to make their competitors do not have time to outbid them anymore.

1.2 Previous Research on Ticket Auctions

The emergence of online auctions has been attracting attention of economists and consumer researchers. It also provides them a rich and huge amount of data to study auctions. Roth and Ockenfels (2002), Ockenfels and Roth (2003), and Ariely et al (2003) conducted empirical studies on late bidding while Schindler (2003) wrote a theoretical paper on the same topic. Related to those studies, Bajari and Hortacsu (2003) tried to explain winner's curse phenomena in online auctions using a structural model. Some other research explores the effect of sellers' uncertainty, which is reflected by sellers' feedback. As recorded by Bajari and Hortacsu (2004), although there have already been abundant of research on auctions' outcomes, those research focused on different features of online auctions.

There have also been several studies conducted specifically on live events' tickets auctions. Bhave and Budish (2014) conducted a theoretical research and develop a model to study the possibility of using auction to sell tickets on primary market. Sweeting (2013) explored the dynamic pricing of ticket resale using data from Major League Baseball (MLB) tickets resale while Leslie and Sorensen (2013) researched on welfare effect of ticket resale using data from 103 concerts in the USA. Both research used the data collected from eBay and Stubhub in their research.

Standard auction theory typically assumes that auctions are independent of one another. Whereas in online auctions setting, competing sellers usually auction a number of highly substitutable goods simultaneously. As a result, buyers have opportunity to choose among many auctions and there is an interdependency of auctions' outcomes. There have not been many studies conducted in this area. Two of the notable research in this topic were conducted by McAfee (1993) and Peters and Severinov (2006) who

develop theoretical models in their studies. The numbers of empirical studies are even smaller. Anwar et al. (2006) investigated the rate of *cross bidding* in a competitive auction environment using data of CPU auctions from eBay while Kayhan et al. (2010) investigated it using Apple ipod auctions also from eBay. In addition, there is yet a case study conducted in this topic using data from Japan concert ticket auction market.

More detailed literature review on auctions and tickets resale in this study will be provided in Chapter 3 and Chapter 4 of this dissertation.

1.3 Research Objectives and Empirical Strategy

1.3.1 Research Objectives

Using secondary market auction data of concert tickets from Yahoo Auction Japan, we attempt to explore the unique features of Japanese concert market and uncover its effects on several auction's properties. To elaborate, In Chapter 3, we examine the effect of seat certainty on auctions' outcomes: success and closing price in the concert tickets' secondary online auction market.

Subsequently, in Chapter 4, relaxing common assumption in auction theory that auction is independent of one another, we examine whether bidders generate 'missed opportunities' in their bidding strategy by not bidding on the auction with the lowest standing bid in a competitive auction setting. We are specifically interested in groups of substitutable and similar auctions offered by competing sellers simultaneously in which there is at least one unsuccessful auction (auction that receives no bids) with lower reservation price compared with closing price of all successful auctions in the competing group, by the time the auctions end. We also explore the size of the 'missed

opportunities' when it occurs and variables affecting both the occurrence and the size of it.

In terms of policy, in Chapter 5, we examine how this common practice in Japan up against more general practices applied in other countries and how it affects the need for regulations e.g. anti-scalping law and consumer protection law.

1.3.2 Empirical Strategy

In order to reach our research objectives, we conducted empirical research using reduced form approach to estimation. Empirical models of auction behavior mostly use a reduced form approach to estimation. However, following Laffont et al.(1995), there have been a number of papers using a structural approach to analyze data from online auctions. e.g. Bajari and Hortacsu (2003) tried to explain winner's curse phenomena in online auctions using structural model. Structural models are attractive because they use game theory to guide the estimation. On the other hand they suffer from two main problems with regard to the subjects in this study. First, they are usually applied to stand alone auctions where the theory is clear. However for most of the tickets on sale in my data, there are substitute goods: auctions for the same concert running at the same time. For this kind of problem there is no clear guidance from game theory about the nature of the equilibrium. In other words there is no structural model to estimate. Secondly, structural models assume that market participants are highly rational and can solve for the relevant Nash equilibria. Whether auction participants do actually play rationally is an open question and one we wish to investigate in Chapter 4. So it seems better to use a reduced form approach which does not impose restrictions on how the auction games are played.

1.4 Contributions

To the best of our knowledge, this is the first study exploring the effect of quality certainty on auction's outcomes. This is also the first study using the Japanese concert ticket market as a case study of product quality certainty. In addition, this is the first study on concert ticket resale using Yahoo Japan Auction data.

There has been considerable amount of research on product quality to date, however they mainly focus on the adverse selection aspect of the case (Akerlof, 1970; Ba and Pavlou, 2002). In contrast, in this study, there is minimal evidence of adverse selection since both sellers and buyers in the secondary market have no knowledge of the seat quality before seat announcement near the concert date and once the announcement commence the quality of the seat becomes known for most sellers and buyers.[6]

Recently, Goncalves (2013) studied the effect of reserve price on auctions's revenue when quality of the goods, in this case football player, is known by both parties using data from football management online game called Hattrick. Therefore, eliminating asymmetric information and uncertainty in product quality. However, to our knowledge, this is the first empirical study using real market data and real good.

In Chapter 4 we find that bidders did not always show rational behavior in their bidding strategy. We contributed to the growing literature of competing auctions by defining several different indicators of missed opportunities. We studied missed opportunities in a market where goods are slightly heterogeneous[7], something that is more close to real life situation. Furthermore, we also found that missed opportunities

[6] In most of the cases, the day tickets are sent to primary market buyers, seat quality also becomes known to most of the sellers and buyers in secondary market.
[7] We later isolates observations into groups where goods are more homogeneous, as what have been done in previous literature in this topic.

are more prevalent as good quality increases, the same was also true for its size. We believe that this relationship has not been explored before in previous studies in this field.

1.5 Organizations

The rest of the paper is organized as follows: Chapter 2 describes and discusses recent developments in Live Music primary and secondary market for Japan in particular and other important regions in general to provide context for the next two chapters. Chapter 3 contains the analysis of the effect of seat quality certainty on auctions' outcomes. Chapter 4 will discuss if this unique feature has an impact of bidders' behavior in competing auctions. Chapter 5 will conclude and provide some policy recommendations.

CHAPTER 2 THE LIVE MUSIC INDUSTRY: A CASE STUDY OF JAPANESE CONCERT MARKET

This chapter will provide an overview of the global music industry that leads to the recent growth in the global live music industry in general, and in Japanese concert industry in particular. It aims to provide context for the next two chapters where we will examine the effect of the uniqueness of Japanese concert ticket markets on ticket auctions' in the secondary market. Therefore, besides the practice and the recent developments in the primary markets, we will also explore the growth in secondary markets.

2.1 Recent Growth in Global Live Music Industry

2.1.1 Sluggishness of Recorded Music Industry

This last decade has witnessed a fall in the world recorded music sales. Once a very profitable market, its sales have dropped from around 30 billion USD in 2003 to less than 15 billion a decade later as depicted in Figure 2-1. The bottom panels of the figure showed the record sales in several major countries in the industry in the recent years and their market shares. The value of the record sales has been decreasing in Japan as well as in Germany and the UK. It dropped in 2010 and came back to the level of 4.5 billion and has been stagnant since 2011 in the USA. It did not change much from the level of 1 billion USD in France. From the figure, we can see that Japan and the USA were the biggest recorded music markets in the world and claimed about 20%-30% of the market each.

2.1.2 Growth In Live Music Industry

While recorded music industry has slowed down considerably in recent years, the opposite was true for the live music industry. Figure 2-2 shows the concert revenue and attendance in North America, Japan, Germany, France, and Australia since 2009 until 2013.[8] We can see from the figure that concert revenue and attendance have increased during that period or have remained stable in those countries.

While North America remained the biggest market in the world, the growth in Japan's concert revenue and its attendance has been remarkable. Japan has even rivaled North America in terms of concert attendance. According to Livenation report, Japan was the second largest live music market in the world.

Table 2-1 shows that while the ratio of Japan's live music annual sales to GDP has always been below 1%, it has increased 2.5 times in the last fourteen years. This phenomenon occurred because the live music industry has been growing much faster than the whole economy in general. While the Japanese economy has been growing annually less than 2% per year on average in the last fourteen years, live music industry has been growing around 8% a year annually on average.

The development in Japan's live music industry has also been happening in other countries. According to the BBC report, live music sales in the UK increased by 17% in 2014. Music industry contribution to total gross value added also increased from 3.5% in 2012 to 4.1% in 2014. In addition, according to UK Music

[8] Although the revenues are in USD, they come from various sources particular to each country. We decided not to show the statistics for the UK although UK is one of the most notable countries in this field because prior to 2011 concert revenues from primary market were combined with ones from secondary markets making it not comparable to other countries.

Survey 2014 (UK Music, 2014), on average, earnings from ticketed concerts accounts for 49% of an artist's earnings. In contrast, royalties from record companies only accounts for 8% of it.

2.2 Japan Live Music Industry

2.2.1 Primary Market

As mentioned earlier, the Japanese concert market is unique. In the subsequent sections we will explore its uniqueness and how it affects the way buyers acquired tickets in primary and secondary markets. We will also examine agents in these markets and market statistics around our observation period.

2.2.1.1 Uniqueness of Japanese Primary Concert Ticket Market

There are several details that make Japanese concert industry unique. Some of the major differences as opposed to what are generally practiced in other countries are summarized in Table 2-2.

The first contrast is that in most cases, concert tickets are sold using a lottery method, be it a full lottery method or a mixed between lottery and first come first served method in general release. Unlike what is generally practiced in North America and in many different countries, instead of using first come first served method which often leads to server overload and crashed websites when high demanded tickets are sold, tickets are sold for the first time to the fans through a lottery method in most cases in Japan. Fans in Japan who want to buy a concert ticket, apply for it either through a fan club, a promoter's website, or a ticket seller website during a period of time. After that

period, fans will receive a notification whether they win the lottery or not. Our sample showed that 93.42% of the tickets are sold through full lottery or mixed lottery method.

Second, concert ticket price is rarely price discriminated in Japan. There are 527 concerts included in our dataset and only in 89 (16.7%) of the concerts was price discrimination applied. Out of these, prices were discriminated into two levels in 71 concerts and only in 18 concerts were more than 2 different levels of price charged. This is in contrast with the data presented in Courty and Pagliero (2008) for the US where in 75% of the concerts price were differentiated and 19% of them had more than 2 price levels. It is clear that Japanese concerts are rarely scaled and therefore, the underpricing problem in Japan is probably more severe than in US, also this problem is even more serious for high quality tickets.

Third, most of the times in Japan, concert tickets are sold without information on the seat arrangement. When you buy a concert ticket in advanced, buyers will not be able to know whether the tickets they are buying are for the section near the stage or for the section on the fourth floor of the stadium. In general, information regarding the seat arrangement is only available after buyers buy the tickets, about 1-2 weeks before the concert date and sometimes the detailed seating information is only available on the day of the concert. Therefore, unless buyers are buying tickets during general release or playguide, they will have to wait for a few weeks to learn about the seating arrangement. Figure 2-3a to Figure 2-4b show the contrast of the experience of buying concert tickets in Japan compared to USA. Figure 2-3a depicts the announcement of AKB48 concert at Tokyo Dome, the ticket price is ￥6,800 regardless where concert attendees sit or if they get to sit at all. Figure 2-3b depicted Tokyo Dome's seating chart which capacity is 55,000 attendees. In contrast, One Direction concert ticket for their Metlife Stadium

concert in Ticketmaster is depicted in Figure 2-4a and Figure 2-4b. Buyers can see that the venue is scaled into 4 price levels, each section has its own price tag and by clicking that section buyers can see the seat available and its price.

When tickets are price discriminated, there is partial information on ticket quality since the more expensive the ticket is, the better the seat quality. However, in Japan, even if the tickets are price discriminated, there is still lack of information about the seating arrangement or the section provided by ticket sellers. Most of the time sellers will only provide information about whether the ticket is for seating tickets or standing tickets (standing tickets are cheaper) or signaled the quality of the tickets by using symbols like SS, S, and A or the position of the seat to indicate the seat quality.

In Figure 2A-1 we can see the example of price discriminated concert tickets. In the lottery presale/pre-reserve, only high quality ￥８，５００ tickets were sold. However, in general release, tickets were differentiated into 3 levels. The designated seats (non-stage side) cost ￥８，５００ as before, the stage side which indicates the seat located near the side of the stage so concert attendees cannot see the stage clearly and comfortably cost ￥７，５００ and the undesignated seat which means they might have to stand and can only see the screen and might not be able to see the stage at all cost ￥5,000.

In addition to those major differences, in Japan, tickets are usually sold through many different channels. Several different ticket agencies, promoters, and even artists' management companies handle the advance sales of concert tickets in Japan. Some tickets are only sold to fan club members and the sales are typically handled by artists' management companies. Some others are sold via promoters' website such as

Diskgarage or Kyodo and some others are sold by ticket agencies such as Ticket Pia, Lawson Ticket, and e+ Ticket.

Also, in most cases, tickets in Japan are sold in several phases. When the full lottery method is employed, tickets are sold only through lottery combined by a short period of a method called play guide. During play guide, fans that want to buy tickets must call a ticket service center to get tickets, therefore it is very hard to get tickets and tickets are usually sold out in couple of minutes. Figure 2A-2 pictured a form describing the steps fans should follow in order to buy tickets for concert with full lottery ticket distribution method in Japanese. Fans should list the days of the concerts they are interested in and pay for the tickets at the bank. A call center is then opened after the application period ended and fans can call it to find out whether they win the ticket or not then a playguide might be arranged afterward. Only highly demanded and famous artists usually employ this method. Similar steps are also applied but with more phases in the case of mixed lottery method. In this case tickets are usually sold through one or more lottery phase followed by a general release during which fans can buy tickets by calling a ticket service center or by buying it online. Figure 2A-3 and Figure 2A-4 show the application schedule for fanclub members and ticket agency members for concert tickets distributed through lottery combined with general release method.

2.2.1.2 Process to Acquire Concert Tickets

There are several ways fan can get concert tickets. However, joining a fan club provides the highest probability to secure a concert ticket. Fans pay a yearly fee of around ￥4,000-￥6,000 to join a fan club but fan clubs member are given priority to get concert tickets first. Also, sometimes tickets are not sold to general public if the

applications of fan club members surpass the number of tickets available or if tickets are only sold through fan clubs exclusively which is the case for several top artists under Johnny's Entertainment and several other famous acts.

When a concert date is decided, fan club members will get a notification, either by e-mail or airmail letter. The mail contains information on the date of the concert, lottery application period/s, lottery result/s notification, general release or playguide if any conducted, and the price of the tickets. Some fan clubs run the process privately so that fan club members have to apply for tickets by sending money in advance via bank transfer. The money will be sent back to the members if they do not win the tickets. Some others cooperate with one of the major ticket agencies and send the web link to that ticket agency's website for fan club members to follow. Therefore, fan club members apply for tickets through the ticket agency and can pay the tickets by credit cards or paying at convenient stores if they win the tickets. Afterwards, the tickets will be sent to winners by letter mail or by printing the tickets at convenient stores about 1-2 weeks before the concert dates. Figure 2A-2 showed the example of pamphlets sent to fan club members regarding concert ticket application. Recently, fan club concert announcements are also sent by e-mail.

Instead of joining each individual artist's fan club, fans can instead apply for promoter's membership. Membership is usually free, however some offers exclusive membership service such as Music Party for Diskgarage and 3A for Creativeman. Fans must pay around ￥4,000-￥5,000 yearly for the membership. However, they are given priority after fan club member to apply for lottery if one of the artists they promote is holding a concert. The lottery for fan club member and promoter's member are usually held around the same period.

As an alternative, fans can also apply for ticket agencies' special membership. Most of concert tickets sold in Japan are sold through three major ticket agencies; they are Ticket Pia, Lawson Ticket, and e+ Ticket. Some artists' management and promoters have exclusive agreement with one of the ticket agencies therefore the lottery phase of ticket selling is only held by one ticket agency but the general releases are mostly done through all three major agencies. Fans must pay a fee to apply for special membership, but they are given priority to apply for tickets both in lottery or general release phase.

The general public can buy tickets from ticket agencies or a ticket box at concert venue. To buy a ticket from a ticket agency, they must register for an account. This registration is free of charge. After fans are registered, they can buy a ticket through lottery applications or general releases. However, there is smaller chance for these fans for winning the ticket compared to previous type of fans.

2.2.1.3 Agents and Trend in Japanese Concert Industry

There are several important agents in Japanese concert industry. They are artist, artist management companies (talent agencies), record companies, promoters, and ticket vendors or ticket agencies. They all play different roles in organizing a concert.

One of the factors that determines the success of a concert and therefore its sales and resale price is the artists. The resale price of a ticket in secondary market for some artists can be more than three times of its original price. Figure 2A-5 contains the list of artists with biggest concert mobilization in the first half of 2013. Bands and idols dominated the list but there were several soloists like Amuro Namie and Hamasaki Ayumi who were in the list. We can also see that several Kpop acts were in the list.

Although it is not always true, artists that sell the most concert tickets tend to do well in records sales as well. Figure 2A-6 depicted the list of top records companies in Japan in 2012. Avex Holdings topped the list, followed by Johnny's Music Entertainment, Universal Music, King's Record, J-Storm, Warner Music, EMI, Victor Entertainment, Toy Factory, and Pony Canyon. This is interesting since local companies are dominating the record market although the sales growth rate for EMI and Warner Music is very high.

When it comes to ticket agencies, there are three major ticket agencies in Japan; they are Pia Ticket, Lawson Ticket, and e+ Ticket. Buyers of concert tickets can buy concert tickets online from their websites or go to convenience stores associated with them to buy the concert tickets there. CN Playguide and Ticketboard.com are other ticket agencies frequently employed to distribute Jpop concert tickets although there are growing numbers of new ticket agencies nowadays.

Although there are numerous promoters in Japanese concert industry, based on the data collected during this study, two third of the concerts in Kanto were held by only ten promoters. Diskgarage managed 99 concerts during observation period that constitutes to almost 19% of the concerts. Other prominent promoters were Kyodo Tokyo, Hot Stuff, and Sogo Tokyo. Also, most of promoters are united in an organization called All Japan Concert and Live Event Promoters Conference (ACPC).

As mentioned previously, there are many concert promoters in Japan; most of them are members of ACPC. The organization was founded in 2011 and its stated objectives are to promote a healthy business environment, to provide education to the public, and to conserve intellectual property rights. In order to meet its goals they conduct survey and research. They also provide workshop and seminars. There are 56

promoters that have become the members of this organization, 22 are in Kanto area. They also have supporting members, which consist of prominent record companies and talent agencies. Members abide an agreement concerning responsibilities in carrying out concerts, how to handle cancellations, safety precaution, how to treat concert attendants, and also resale of concert tickets.

Since one of the objectives of ACPC is to conduct research, they provide some statistics on Japanese concert industry. Although these statistics are not nationwide since not all promoters are member of ACPC they provide big picture of the concert industry in Japan.

From Figure 2-5 we can see that there is a steady increase in the number of live performances held in Japan over the last 5 years. There are in total 20,044 live performances held in the year of 2012, which is the year our observation took place. The number of mobilization and the total sales revenue from concerts has been increasing as well, as described in previous section and depicted in Figure 2-6. There were 32.88 million people attending concerts in 2012 and the revenue gained was ￥170.14 billion. This figures showed that the trend in Japan is different from what happened in the United States, as reported by Krueger (2005). In United States, the increase in revenue comes from the increase in price since number of concerts was stable and the attendance was declining prior to 2011. In Japan, attendance and revenue seem to have similar upward trend.

There is no official data on the average price of concert tickets, however by dividing total sales by attendance we can get the average sales per attendant. The number is quite stable over the years, that is around ￥5000 although it has fluctuated more since 2011.

Table 2-3 displays the number of performance, concert mobilization, total sales (revenue) from concerts, and average total sales per attendant for Kanto area in 2012, the year our data was collected.[9] This study will focus on concert ticket resale in Kanto Area since the area has the most active primary and secondary concert tickets markets in Japan.

2.2.2 Secondary Market

2.2.2.1 Regulations Governing Secondary Concert Ticket Market

Reselling and buying concert tickets online in the secondary market fell into a gray area in terms of legality. According to Tokyo Metropolitan Area Ordinances, trading tickets in a public area and a public transportation, which include concert venue, is against the law. However, there are no rules that govern the online secondary concert tickets trade and it is also unclear whether the Internet is included in the definition of public area. Also, according to this regulation, reselling and buying of tickets concerts in ticket shops are not against the law.

Although engaging in secondary concert tickets trade is not against the law, when fans buy tickets from fan clubs, promoters, or ticket agencies in primary markets, they are agreeing to a contract and most types of engagement in secondary concert tickets trade are violating this agreement. Reselling tickets in order to get profits are against the Purchase Agreement. It is not clear if tickets are sold not to gain profits, however reselling tickets in on line auctions are also against this agreement. If a fan club member is discovered engaging in scalping activity, he/she risked being charged with criminal activity. If he/she is discovered reselling tickets to a third party for profits

[9] We use the term mobilization and attendance interchangeably in this study.

for example by selling it through an online auction, his/her membership will be terminated. Also, buyers who buy from a third party might risk being denied entry to concert venue or being evicted from the venue. A similar agreement takes place when fans buy from promoters and ticket agencies. In addition, promoters who are members of ACPC must agree to an agreement that ticket buyers are forbidden to transfer tickets bought from these promoters to third party for profits, or to resale the tickets on online auctions, or to buy tickets with the purpose to resale them to third party. Those promoters also agree that concertgoers who purchase from Internet auction or bulletin boards/social media sites or ticket shops or scalpers will not be let into the venue.

Basically, reselling tickets for profits are violating the agreement between buyer and seller, so are buying and selling concert tickets through online auctions, ticket portals, or social media like Twitter and Mixi. Figure 2A-7 showed some clauses of Concert Tickets Purchase Agreement for Johnny's Entertainment artists, which is one of the biggest entertainment companies in Japan in English. It contains Johnny's Entertainment's policy regarding ticket resale.

There are already some measures taken by concert organizers in Japan in order to limit resale recently. Some recent concerts use electronic tickets instead of paper tickets; therefore it is nearly impossible to resell the tickets. With this method, tickets are sent to mobile phones and buyers are asked to show it in order to enter the venue. Furthermore, the ID on the tickets must match the ID of the attendant in order to gain entry. One of the concerts employing this method is SMTOWN in Tokyo Special 2013. Previously, if concerts were held in small venues like Halls or Clubs, organizers might check whether the attendants ID matched the one written in tickets, in this case, fans buying from third party might not allowed entrance to the concert venue. In contrast, ID

checks are rarely done if concerts are held in big venues since it is not effective and takes time. However, recently, ID check seems to be conducted more frequently. Concerts by Johnny's Entertainment artists and AKB48 have buyers' name written on the tickets and concert organizers perform ID checks although their concerts are usually done in large venues. Furthermore, some concerts nowadays required buyers to register the name of their companions when they buy concert tickets to further prevent resale when they buy or win more than one tickets.

In some other concerts, seating information is only released on the day of the concert. Before the concert date, buyers in primary market received partial information of the seating arrangement such as the floor and the limited information on the section of the seat such as the gates however the real ticket containing detailed information of the seating arrangement are only released when buyers enter the venue. Concert attendants who enter the venue have their tickets scanned and exchanged with the real seating arrangement. This way, they hope it will dampen the resale and rent seeking occurred in secondary market since one of the motive that drives people to buy from secondary market is to get tickets with better seating arrangement. Some concerts that used this method are Bz concert in Tokyo Dome and Kim Jae Joong concert in Yokohama Arena. Figure 2A-8 provides examples of this approach. The only information we can get from the temporary ticket is the base where the seat is located and the gate but there is no information regarding the row and seat number. The information regarding the row and the seat number as pictured on the bottom panel is only given by the concert organizer at the gate of the venue on the concert day. Also, fan clubs tickets usually have members' name and ID written on the tickets.

All these precautions are in contrast to the developments in North America. Recently, Ticketmaster, which dominates concerts tickets primary market, allows its tickets buyers to resale their concert tickets as long as they do it in secondary market developed by Ticketmaster. This contrast might be due to the reluctance of Japanese concert organizers to be perceived as gouging the fans.

2.2.2.2 Acquiring Concert Ticket in Secondary Market

There are some places both physical and virtual/online secondary markets in Japan where people can sell and buy tickets. First, you can always buy or sell tickets at the concert venue or near the venue on concert date, there are many people still doing this act although it is classified as scalping activity and punishable by law. The attraction of buying from scalpers near concert venue is that you can bargain and the tickets can be much cheaper because as the concert time goes nearer usually scalpers are offering cheaper price to make sure all the tickets in their possession are sold out. Second, there are many concert ticket shops scattered around Japan. Most of these shops have fixed price so that it is hard for buyers to bargain, however shop owners usually lower their price on the concert date.

The increasingly popular way to buy and sell concert tickets due to the advancement of the Internet is by online trading. Fans can buy and sell their tickets through online auctions or through online tickets shops and portal, which offer tickets with fixed price. Recently, with the rise of social media fans also trade and exchange tickets through social media like Twitter and Mixi.

Fans and professional traders can also put their tickets for action on online auction site. The most popular online action site for concert tickets in Japan is Yahoo

Auction Japan from which the data for this study are collected. During our observation period, concert tickets auctioned in Yahoo Japan Auction comprised of around 85% of all concert tickets auctioned online. Other prominent auction sites in Japan are Rakuten Japan and Mobaoku.

In Japan the amount of websites where fans can buy ticket at fixed price has been blooming recently. Some of the notable ones are ticket.co.jp, Ticketstreet, and Ticket Camp. Fans who want to sell their tickets can fill up the form in the website, ticket center will then contact them to check whether their ticket is not counterfeited. After they post the tickets in the websites, if the ticket is sold then the ticket center will notify them and they will have to send the ticket to the buyer. The commission for ticket center is around 10% of the price of the sold ticket including the shipping cost. On the other hand, buyers can browse and buy ticket from the website and felt relatively safe since there is a check mechanism done by the ticket center. The commission needed to pay by buyers depends on the price of the tickets. It ranges from ￥420 to around 5% of the ticket's price. This mechanism is similar to the one applied by StubHub which is the largest online market place for resold tickets in United States. Although ticket price is fixed, this posted fixed price might be lower, equal, or higher than the face value. Generally, price of the ticket is higher than the face value for popular concert and better seats. Sellers may repost their tickets and change the price if they aren't sold on the first try.

With the rise of social media, there are more and more fans buying, selling, and exchanging tickets through social media. Fans who want to sell their tickets for some reason can post the detail of the tickets they are selling such as the date, venue, and number of tickets they are selling on their SNS account. Fans who need ticket can also

post the date and the name of the concert the tickets they want on their twitter account or send message to other fans or professional seller who post in their account that they have tickets to spare. One of the unique features of ticket trading through social media is that it allows barter, which doesn't involve money at all. Often times, concerts are held in a city or even a concert venue for more than one time. Fans who have tickets for one particular day might not be able to come in that particular day and hope that they can exchange their tickets with tickets for other days. This phenomenon is more prevalent in Japan compared to other countries since tickets are sold by lottery in primary market. In most cases fans can apply to buy up to 4 tickets for each day of concerts and for at least 2 days of concerts in primary market. Therefore, they can apply for 4 tickets for at least two days of the concerts even though they probably need fewer than 4 tickets for each concert day. In this case, if they win lottery for all days they can later sell the remaining tickets they don't need in secondary market. Otherwise, if they only win for one day they can barter the remaining tickets they don't need with tickets for tickets for other day if they wish to attend more than one concert. In a way, this is a better way to acquire tickets especially for popular concerts that sells for very high price in secondary market. This way, they can exchange tickets for its face value instead of buying tickets for very high price in secondary market. They can also sell the remaining tickets in the secondary market and use the proceeds to buy tickets for concert on other day. Figure 2A-9 shows the example of this phenomenon.

2.2.2.3 Yahoo Japan Auction

The data used for analysis in this study comes from Yahoo Japan Auction. This site is the largest online auction site in Japan. It was started by Yahoo in 1999. In order

to participate in an auction, buyer and seller must first register and obtain Yahoo ID. If auction is successful, seller must pay 5.25% winning fee while there is no fee needed to be paid for buyer. However, buyer and seller who intend to engage in trade with price of goods higher than ￥4,999 must obtain Yahoo Premium service that costs ￥399 per month. For sellers, exhibition up to 10 times per month is free but they will need to pay ￥10.5 per exhibition for the 11th and the rest exhibitions. The minimum bid increment in an auction can be found in Table 2A-1. There is also an optional relisting option if the auction receives zero number of bids. Sellers can set lower minimum bid automatically for the next option. In the case where an auction is relisted after receiving zero bids, the auction ID will be the same. There is a price cut negotiation option for auctions with minimum bid higher than ￥4,999.

The rating or feedback system in Yahoo Japan Auction is a bit different from eBay's format. The seller feedback rating shown in the auction page in Yahoo Japan auction includes not only rating as a seller but also as a buyer, however buyer rating are usually only a small portion of overall rating.

Similar to some auction features in eBay. Sellers can put Buy It Now (BIN) option in their auction and put on hidden reserve price. However, unlike in eBay, BIN option does not disappear once a bidder put a bid in the auction.

There is also an auto extension option that sellers can apply. When applied, auction is extended for five minutes if there is a bid and increase in price in the last five minutes of an auction. If there is an increase in price during this extension period then auction will be extended for another five minutes. This feature of Yahoo Auction made sniping harder to do compared to in eBay.

Yahoo Japan Auction is also the biggest place for concert ticket auction. To find concert tickets in the site, buyers can use category search. The most important information for a concert tickets' auction page is usually contained in the title. The information about concert date, venue, artist, type of tickets, number of tickets, and seating detail when available are usually contained in the title although it is explained in more detail in the description section. Other information available are auction ID, current price, number of bids, minimum bid, Buy It Now (BIN) option when available, the start and ending of an auction. Sometimes, concert tickets are auctioned in pairs. If tickets are auctioned in pairs then quantity equal to one means that there are two tickets available but buyers who are interested must buy both tickets and the prices are for 2 tickets. Sellers can put up to three pictures on their auction page, sometimes picture of the tickets sold or e-mails confirming that sellers have the property right for the tickets are posted, but sometimes there is no picture or the picture is only the poster of the concert. There is an indicator if auction is successful or not but observers can only see partial name or ID of the successful buyer. Information on sellers that are disclosed is sellers' Yahoo user ID, their rating/feedback score, and the place of the goods (prefecture). Figure 2A-10 and Figure 2A-11 show the example of Yahoo Japan Auction pages.

The concert tickets for this study are limited to Japanese Pop (J-POP) concert tickets for concerts in Kanto Area. J-POP genre is selected for this study because the unique practice in ticket selling is more prevalent in this genre. The study is limited to Kanto Area since concert ticket market in this area is the largest in Japan and author is more familiar with the practice of ticket selling and secondary ticket market in this area. In order to find tickets with this features in Yahoo Japan Auction, buyers can choose

from the category menu Auction> Tickets, Voucher, and Hotel Booking> Box Office Ticket> Music> Japanese pop> Kanto.

Figure 2-7 to Figure 2-9 show some statistics on auctions outcomes for concert tickets auctioned at Yahoo Japan Auction. The data for these statistics come from Aucfan.com, a company providing data and other services concerning online auction in Japan in general and Yahoo Japan Auction in particular.

Figure 2-7 showed that total revenue from successful auctions has been increasing in the last four years. Despite the increase, its ratio to total primary market concert revenue reported by ACPC has decreased over the same period. There are some possible explanations for this. First, the share of other secondary ticket markets has increased and it is possible given the increasing number of new websites offering resold tickets. Second, there is an increase in non-ticket revenue recently.

Figure 2-8 depicts the number of successful transactions and total revenue in Yahoo Japan Auction for JPOP concert tickets in Kanto area in 2012, the year we conducted our data collection. We can see that they are highest in December and April, which coincide with numerous year-end concerts and spring concert. The monthly number of successful transaction is ranging from about 16,000 to 38,000 per month and the average monthly revenue is ranging from ￥259 million to ￥756 million. From Figure 2-9 we can digest that the monthly average transaction price reach its highest in September when it reaches ￥21,402 and it is lowest in October that is ￥12,829.

Figure A2-12 to A2-14 describe Yahoo Japan Auction resale ticket transactions in July 2012 that coincides with the observation period for this study, by the hours of transactions, the day of the week, and the prefecture where concerts occurred. From Figure A2-12 we can see that about 69% of all auctions in July 2012 ended between

10pm to 12 am, the number is the same for successful auctions. The rate of success is ranging between 61% and 87%, the highest rate occurred on 12am and the lowest occurred on 4pm. The average closing price is around ￥15,000, the highest average closing price is reached between 12am and 1am. There is a similar pattern between rate of success and number of bids, they increase from 8pm until 12am and go downward after 12am.

Figure A2-13 shows that most of the auctions ended on Sunday until Tuesday and it is the same for successful auctions. Since about two third of the auctions in Yahoo Japan Auction for concert tickets have 1 day or 2 days duration, it seems that people sell their tickets during weekend and the auctions go on until Monday or Tuesday. The average closing price goes down from Sunday to Tuesday where it is at its lowest point but it reaches its highest peak on Wednesday before it goes down again on Thursday when the average bids is also at its lowest point. However, there are only slight differences in average closing price from day to day in a week. More than two third of the ticket auctions occurred for concerts in Tokyo area as depicted in Figure A2-14.

Meanwhile, more than 90% of the sellers for concert tickets in Yahoo Japan Auctions are individuals as portrayed in Figure A2-15. The rate of success for auctions with BIN option is lower than the auctions without BIN auction. The lowest rate of success occurred for store owned BIN auctions. However, the highest rate of success is achieved by store owned traditional auction. It is likely that storeowner has more experience in how to successfully sell tickets while the combination of BIN method and store owned seller is unattractive for ticket buyers in the secondary market. Contrary to what we might assume, the auctions held by individuals generate higher closing price

than the ones held by stores. It will be interesting to see why it happens. Based on study by Sweeting (2012), fans and inexperienced sellers are more likely to ask for higher price since if they can't sell the tickets they can still use the tickets for their self. We can also see from the figure that in auctions with BIN option price tends to be lower than in non-BIN auction, they also receive fewer average bids compared to non-BIN auctions. As expected, the average number of bids for auctions with BIN option is lower than the auctions with no BIN option.

2.3 Impact of the Uniqueness on Japan Concert Industry on Secondary Market Concert Ticket Auctions

According to the study done by Krueger and Pray (2008) for USA, most people stated that they went to the secondary market to buy tickets with better seats from reseller. The second and third reasons stated they bought from secondary market because the tickets they want were sold out in Ticketmaster and because they were unsure of their ability to attend the concert. Moreover, based on the study done by Sweeting (2013), Krueger and Pray (2008), and Leslie and Sorensen (2013), seat quality significantly affected current price of a ticket in an auction. They found that the better the seat quality, the higher the resale price. Previous studies also found that success in an auction are significantly determined by seat quality and that best seats have the highest resale rate.

However as explained previously, in Japan, tickets in primary market are generally sold without information of the seating arrangement, at least for a period of time. Therefore, there is a period of time when tickets without details of the seating arrangement are resold in secondary market. Figure 2-10 describes the general activities

occurring in Japanese Market. As we can see, from the time that the results of lottery announced and buyers find out whether they win the ticket or not (step (3) in the chart), tickets can be sold in secondary market by those winners. However since seat information is usually released much later (step (9) in the chart), those tickets lack of seating information and can be perceived as homogenous in quality.

There can be several reasons why people buy and sell this kind of tickets. Some sellers that are buyers who won the tickets in primary market might found that they cannot attend the concert and decide to sell their tickets as fast as possible. Some other might found that they won tickets for some day but not for all the days of the concert that they want. Waiting until the seating details are released might be too risky for them if they want to buy tickets for the days they didn't win since they risk receiving tickets with bad seats for the tickets they won, which will not sell for much. In buyers' side, some buyers might just decide to buy tickets without knowing the seating arrangement and try their luck since buying tickets with good seats after the seating arrangement are released will be too expensive for them. Or they just want to secure the tickets as fast as they possibly can to make sure that they can attend the concert.

As mentioned previously, seat quality is a major driver for buyers in secondary market based on various studies. Therefore, we would like to explore its effect or the lack thereof on auctions' outcome. Chapter 3 will investigate the effect of seat quality certainty and other variables on auctions' success and on final price. In Chapter 4 we will explore if bidders missed some opportunities or made mistakes in their bidding strategy in this market. We will also investigate what affects it. Seat certainty is again one of the factors explored.

CHAPTER 3 THE EFFECT OF CERTAINTY ON AUCTION SUCCESS AND CLOSING PRICE: A STUDY OF JAPANESE CONCERT TICKET RESALE MARKETS

3.1 Introduction

Ticket markets for entertainment and sports events are different from the textbook market model in several ways; for example, each seat provides different quality of experience for the concertgoers, so that the goods are not homogenous. This nature provides an opportunity for promoters to differentiate the price of the tickets based on the seating arrangement. The practice is usually known by scaling the house (Courty, 2000). In addition, event tickets are perishable goods so once the event takes place, the ticket has no value anymore. However, despite recent increases in concert ticket prices, promoters often sell ticket at underpriced rates. Finally, unlike ticket for some transportation industries (e.g. airplane ticket), ticket for entertainment and sports events are usually transferable, therefore it can be resold in secondary market.

This study investigates the market for ticket resale in Japan using a unique dataset constructed by the author from Yahoo auctions – the main venue for ticket resale. It includes an overview of how the market operates, but it is particularly focused, first on the determinants of success in the auction of concert tickets in Japan and secondly on the determinants of closing price of concert tickets.

There are several reasons why ticket resale may take place. First, since tickets are in high demand and promoters often choose to underprice the ticket, there is an incentive for brokers and general consumers to buy tickets in the primary market and resell it later with higher price to consumers who cannot buy it from the primary market

(Krueger (2005), Leslie and Sorensen (2013), Eckard and Smith (2013)). However, it seems that it is not the sole reason why ticket resale may occur. According to the report by Billboard Boxscore Research in Courty (2003b), ticket price for entertainment and sports events has been rising in recent year and only 39% of the concerts in United States were sold out in 2001, yet the secondary market for concert and sport events tickets still flourished. Another alternative reason is that although each seat offers different quality of experience, promoters do not charge each seat differently despite their monopoly power, instead they usually divide seats into several categories and charge each category accordingly. When the event is not fully scaled, there is an opportunity for arbitrage. As a result, agents in secondary market interact and price each seat differently according to market forces (Courty and Pagliero (2012a), Courty and Pagliero (2012b)). Other reason might be that some consumers do not know whether they can attend the event or not by the time the tickets are sold in primary market but find out later that they can and want to attend the event therefore creating demand in secondary market (Krueger and Pray (2008)). Finally, some buyers that already buy their tickets in the primary market might find out later that they cannot go to the event so that they need to sell the tickets in secondary market (Courty, 2003). Based on the reasons stated above, from economic point of view, resale is welfare enhancing since voluntary trading leads to more efficient allocation. Nevertheless, resale seems to have negative stigma in general. Promoters, artists, sportsmen, and even some of the consumers stated frequently that they disliked resale. One of the reason could be that sellers in secondary market often demonstrate rent seeking behavior or scalping which leads to much higher ticket price in secondary markets compared with the one in primary markets. Some sellers also sell counterfeit tickets, which might affect the

reputation of promoter or artist that organize the event. As a result, resale is forbidden or regulated by government in many places.

As well as being the second largest concert market in the world, the concert ticket market in Japan is unique in many ways. First, in addition to being underpriced, ticket sells are rationed. In order to get the right to buy concert tickets of major Japanese artists in advance, in most cases buyers have to join the artists' fan clubs or buy promoters' membership in order to apply for lottery among fans to get the tickets or join the rest of general public to buy it from major ticket distributors with smaller probability of winning. In addition to that, promoters for Japanese artists' concert do not announce the seating arrangement until about one week before the concert. Since the primary market takes place about one until two months before the concert, buyers in primary markets do not know about the seating arrangement when they buy the tickets in primary market. Therefore, they have no information on the quality of the product that they buy. This practice is the opposite of what normally occurs in recent years in USA where buyers can select not only the section but also the exact seat in the concert venue. Nevertheless, this is not the only occurrence in Japan where sellers or event organizers delay or shroud the quality of the goods being sold. Yamamura (2011) investigated the effect of non-announcement of starting pitcher in Central League of Japanese Professional Baseball League on game attendance while Chaikal (2015) explored the practice of Fukubukuro. [10]

Although buyers for Japanese concert tickets do not know about the seating arrangement until near the concert date, since the lottery process is carried out months

[10] Fukubukuro (or lucky bag) is a familiar retail institution in Japan and other countries for disposing unwanted stock during New Year sales. In fukubukuro, retailers bundle goods into bags. General information about the contents is provided, but details of brands and specifications are concealed.

in advance before the general release, some of them know whether they win the ticket or not prior to the announcement of the seating arrangement. As a result, some sellers and buyers of the tickets in the secondary market engage in trades while having no information about the seating quality for some period of time. Finally, Unlike in USA where the promoters often scale the venue into several categories, many Japanese concert venue are not scaled, and if they are scaled, the promoters usually only scale it into 2 or 3 different price categories.

Buyers and sellers of concert tickets in secondary market engage in trade through various ways. Some buy and sell tickets at fixed price and some other trade through auction. While physical shops still exist in many places in Japan, the Internet makes it easier for them to trade via online shops. There are several online auction sites where tickets are resold; however the biggest auction site in which concert tickets are resold and bought in Japan is Yahoo Japan Auction.

Using secondary market auction data of concert tickets from Yahoo Auction Japan, there are two aims to this study. First, this study will investigate what are the determinants of success in the auctions of concert tickets in Japan, especially the effect of certainty in ticket quality on auction's success. Second, this study will examine the determinants of auction closing price of concert tickets in Japan , including the effect of certainty in ticket quality on auction's closing price.

The major contributions of the paper are as follows: first, to the best of our knowledge, this is the first study exploring the effect of quality certainty on auction's success and closing price. In addition, this is also the first study using the Japanese concert ticket market as a case study of product quality uncertainty. Third, research in

product quality to date mainly focuses on the adverse selection aspect of the case.[11] However in this study there is minimal evidence of adverse selection since both sellers and buyers in the secondary market have no knowledge of the seat quality before seat announcement near the concert date and once the announcement commence the quality of the seat becomes known for most sellers and buyers. Finally, most studies on consumer auction data focus on eBay. This paper adds to the very small number of papers that use data Yahoo auctions, which has significantly different institutional rules compared to eBay as described in Chapter 2.

The next section will contain the literature on auctions, ticket markets, and uncertainty in product quality. Section 3 will explain the data, sampling process, and some descriptive statistics of the variables. Section 4 will explore the model specification and estimation techniques. Section 5 will contain the results. Section 6 will conclude and suggest some policy recommendations.

3.2 Literature Reviews

3.2.1 Related Literature on Price Determinants in On-Line Auctions

The study done by Bajari and Hortacsu (2003) is one of the earliest and most influential studies on online auctions. Using data from eBay, they attempted to quantify the "winner's curse" and to explore what factors influence bidding behavior and entry, especially the effect of reserve price.

In order to answer these questions they collected data on US mint/proof coins auctions on eBay between September 28 1998 and October 2 1998. Furthermore, they

[11] Menik and Alm (2002), Livingston (2005), Lucking Reily et.al (2007), and Liu et al. (2013) assume that auctioneer know the quality of the good whereas bidders do not know if the unformation provided by auctioneer is accurate or not.

also collected book value information of the coin sets from November 1998 issue of Coin magazine. They found that bidders updated their bids frequently and bids were concentrated at the end on the auction period and bid levels were declining on number of bidders.

Based on these findings, it was concluded that private values framework could not explain this behavior. Reduced form OLS regression was performed to estimate the extent of winner's curse and determined factors affecting bidding behaviors. Furthermore, structural model estimated with Bayesian method to overcome endogeneity bias.

Based on linear regression result, the winner's curse effect is 3.4% of book value per additional bidder and average profit margin is 4.2%. Minimum bid, blemish, and experience affect bid value significantly while the effect of secret reserve price is moderately significant. However as mentioned before these results can only be treated as suggestive. The results of structural model are not very different from the reduced forms. Winner's curse based on this model is 3.2% for each additional bidder.

Dewan and Hsu (2004) aimed to investigate the presence and extent of adverse selection in online stamps market by comparing behavior and price in eBay stamp auctions and specialty stamps auction site Michael Rogers. They also estimated the effect of sellers' reputation on probability of sale and natural logarithm of closing price using data from eBay. Data was from January 2000 to September 2000 and they ended up with 9,944 observations.

The equation for probability of sale was estimated with probit. It showed that log seller rating had positive and significant impact on probability of sale. Other variables that affect probability of sale were logarithm of book value, logarithm of

starting bid, logarithm of auction length, and dummy variables for international transactions, weekend, and secret reserve price. The price equations were estimated using OLS technique and censored normal Tobit regression. However, the OLS estimates were biased since it did not have correct functional form. The Tobit result showed that log seller rating had positive and significant impact on log closing price. Other significant variables affecting closing price were log number of bids and dummy variable for weekend.

The study done by Dewan and Hsu (2004) provides more information on what variables affect probability of sale and auctions' closing price. However, is log number of bids, which is a covariate in the Tobit regression is likely to be endogenous, therefore the result of the regression might be biased.

Lucking Reily et al. (2007) analyzed the determinants of price in online auctions using eBay auction data for collectible one-cent coins. They used programming language *Perl* to collect data from eBay pages. Data was collected on US cents auctions from July 1999 until August 1999 and they ended up with 20.292 observations. However, only 461 observations of US Indian Head Pennies minted between 1859 to 1909 were used for the modeling since only this subset of the data have complete information on the book value of the coins.

The natural logarithm of closing price was employed as dependent variables. The explanatory variables include natural logarithm of book value, natural logarithm of minimum bid, dummy variable of secret reserve price, natural logarithm of positive rating, natural logarithm of negative rating, length of auctions, and weekend dummy. The econometric method employed by the authors is censored normal maximum likelihood estimation procedure. It is similar with Tobit regression, however, censoring

point in this case minimum bid, changes across observations.

They corrected for the omitted variable bias by including book value in the regression and run the regression using subset of the observations. They found that, the coefficient of natural logarithm of book value is 0.81 and significant, indicating higher valued coins' auction prices tend to be relatively lower fractions of book value. One percent increase in positive rating yields 0.03% increase in price while equal change in negative rating yields 0.11% decrease in price.

The study done by Lucking Reily et al. (2007) provides us with alternative econometric methods to OLS in order to explore variables determining closing price. It also employed more variables than what are employed in model developed by Bajariand Hortascu (2002). Based on their results, book value is an important determinant of closing price without which the result suffered from omitted variable bias. Also, the study explored scenarios in which minimum bid affects closing price in different way.

Livingston (2005) argued that the previous works on the effect of reputation on closing price were biased downward. The reason is that they did not use appropriate functional form to capture the effect of reputation. To capture the diminishing marginal effect of reputation he divided the distribution of good records held by each seller into quartiles, he then created dummy variables, which indicate whether each auction falls into each quarter. In addition to that, he also argued that OLS is not an appropriate method to be employed to estimate the effect since due to sample selection bias problem. In order to overcome this problem he used Heckman sample selection method using Full Information Maximum Likelihood (FIML) to estimate both selection equation and bid (closing price) equation. Furthermore, he created dummy variables based on level of normalized value of minimum bid and presence of secret reserve price and employed

them only in selection equation. Theory suggests that minimum bid and reserve price affect participation decision but not how much you bid.

To test the model, Livingston (2005) collected 861 observations between October 20th 2000 and August 20th 2001 on eBay auctions of Taylor Made Firesole irons, a variety of golf club. The results showed that a good report has a positive and significant impact on whether a bid was placed or not indicated by the positive and significant coefficients of all the dummy variables. Higher minimum bid ratio leads to lower probability of participation while the opposite was true for secret reserve price. Other variables that significantly affect selection are fraction of bad reports and variables describing golf club characteristics such us dummy variable indicating whether the club was new. The result of bid equation estimation showed that good report has positive and significant impact on the amount of the highest bid as indicated by the positive and significant coefficients of all the dummy variables. Not only that, but the magnitude of the coefficients are higher than the result of Tobit and OLS estimations. This confirms that the previous works done in this field had undervalued the effect of good reputation. Other variables that significantly affect closing price are dummy variable indicating whether the auction ended at midnight until 4am, book value of clubs, and variables describing golf club characteristics.

The study done by Livingston (2005) provides us with alternative econometric methods to OLS in order to treat possibility of sample selection bias. It also showed us the importance of employing correct functional forms to see the true effect of variables determining closing price in an auction.

Liu et al. (2013) compared the bidding behavior in Japan and Taiwan. They examined the returns to seller's reputation and the impact of auction characteristics on

auction closing price in online market. They collected data from Yahoo Japan Auction and Yahoo Kimo Auction (Taiwan) on Apple iPod Nano MP3 player online auctions from October 1st 2066 to November 30th 2006 by hand. They successfully collected 1953 and 727 observations from Japan and Taiwan respectively.

They employed a bivariate sample selection model using Heckman two-step estimator (Heckit) procedure to test their model. Variables *sniping* and *extension* are only used in participation equation. In Japan and Taiwan an auction can be extended by 10 minutes if two bids are received in the last five minutes of an auction, if this option is available, variable *extension* equal to one and zero otherwise. Variable *sniping* is equal to one if a bid is placed in the last five minutes of an auction.

The participation equations' results showed that the estimates for negative (positive) scores in win equation are mostly significant in Japan (Taiwan), showing different influences of reputation on probability of sale in those 2 countries. Probability of sale decreases with larger capacity of the device while prompt responses from seller displayed opposite effect. Also, shipping and handling fee decreases probability of sale in Japan but not in Taiwan. The price equations showed that reputation variables are jointly significant. Positive reputation has positive and significant impact on closing price in almost all equations in both countries. However, non- positive reports only affect price in Taiwan. Other variables that significantly affect price in both countries are length of an auction and Buy It Now (BIN) options that tend to increase price. Weekend effect is significant in both countries, however the sign is positive in Taiwan and the opposite in Japan. Also, shipping and bonus do not affect price in Taiwan while they tend to increase closing price in Japan.

The study done by Liu et al. (2013) is the first study providing insight on the

effect of culture on on-line auctions' probability of sale and price determination. It also employed data from Yahoo Auction Japan, which is rare.

Similar to the study done by Liu et al. (2013) this study will also use auction data from Yahoo Auction Japan. As mentioned earlier, this study will be different from these previous works in several ways. First, the object studied is concert ticket that is perishable. Second, it will include certainty in seat quality as one of the explanatory variable.

3.2.2 Past Studies on Ticket Resale

Resale generally has been studied extensively in auction literature. Che and Gale (2009) showed that random assignment followed by resale market might result in higher welfare than market assignment followed by resale. Hafalir (2006) studied how allowing buyers to resell to each other can either increase or decease nonlinear pricing monopolist. The decrease or increase in profits depends on utility specification and costs structure.

When a firm or a promoter underprices and rations tickets by a lottery system, Thiel (1993 in Courty (2000)) showed that the existence of brokers in resale markets allow consumers who value the performance the most but who did not win the lottery to get the tickets from consumers who have lower valuation but win the lottery. Therefore, resale is welfare enhancing. In addition, resale restriction increases welfare only when it completely eliminates resale market. On the other hand, Diamond (1982) concluded that resale results in unavailability of tickets at advertised price, which often damages the goodwill of the performance and tends to create accusations of fraud and complicity against promoters.

Courty (2003a) modeled a situation where some consumers prefer to plan in advance, while others have to wait until last minute since they will not find out until then whether they can join the concert or not. Under this condition, he showed that the only equilibrium occurs when promoter sells ticket early to capture diehard fans, which creates profits opportunity for brokers. Promoters cannot capture profits earned by brokers and deter them from entering. Furthermore, he argued that promoters may choose to prohibit resale since allowing resale changes early consumers' willingness to pay.

Many economists have provided theories to explain why promoters choose to underpriced tickets. Becker (1991) explained that tickets may be underpriced because artists gain utility playing in sold out venue, or because attending a full house event provides more enjoyable experience for the audience. Other reason why ticket is underpriced is because promoters or artists want to be fair or assure access for all their fans since audience value being treated fairly (Kahneman et al. (1986)). Other reason why artists choose to use uniform price according to Courty and Pagliero (2012b) is because they have a different revenue model. Some artists have high proportion of revenue from music sales and care more about long run profit. Some others have high proportion of revenue from merchandise. For them, public image is important. Recent theoretical studies by Courty and Nasiry (2015a), Radoias (2015), and Chen and Cui (2013) show that applying uniform price is an optimal strategy under those conditions.

Although there are numerous theoretical studies in ticket resale, there are not many empirical studies done in this field. Leslie and Sorensen (2013) studied the determinants of resale activity and the welfare effect of resale specifically for ticket markets. They found that resale takes place when there is a general under-pricing of

tickets in primary markets, un-priced seat quality, late arrivals, and schedule conflicts. Using the data from music concert primary and secondary market in United States they also found that resale activity increases allocative efficiency. However, half of this increase in welfare is offset by increases in costly effort levels in the arrival game and transaction costs in the resale market. Two of the empirical literature that covers ticket resale comprehensively were done by Sweeting (2012) and Krueger and Pray(2008).

Using data from secondary market for MLB tickets, in his paper Sweeting (2012) showed that sellers of perishable goods cut price, as day of the game grows nearer. He employed data from two biggest on-line secondary markets for MLB tickets (StubHub and eBay) to test whether sellers that consist of both fans and professional brokers price dynamically and found that prices fall by 30% or more in the month leading to the game day irrespective of the types of mechanisms (fixed price and auctions) and type of sellers. He also found that probability of sales increase at the same time. He argued that this behavior adopted by sellers due to dynamic incentives alone since he controlled for ticket quality and demand shock which summarized in residual demand curve that changed very little during the that period.

Ticket listings are perishable products and it is also a differentiated one in the sense that numerous listings of the same game in on-line secondary market are different in the quality of the seat, number of tickets included, and reputation of the seller in the case of eBay listings. The author stated that differentiation might play two major roles in supporting price decline as an equilibrium outcome. First, it provides sellers with some degree of market power that enables them to set a mark-up over face value, which can be adjusted over time. Second, it may prevent strategies that exploits and arbitrages away price decline.

Sweeting (2012) used secondary market data from StubHub and eBay on regular season MLB games in 2007. The StubHub data contains fixed list price from the website 'buy' page for each game each day from January 6th, 2007 to September 30th, 2007 which is collected using automated scripts. In the end, 637,217 eBay fixed price listings and 298,128 auction transactions were collected between January 1st, 2007 and September 30th, 2007. The author also collected primary market data such as game fixed effect, time performance variables, and face value of tickets for each game, section and row.

The author employed the regression model below to estimate price path of secondary market MLB tickets:

$$p_{it} = D_t\beta_t^D + F_{it}\beta^F + C_{it}\beta^C + Q_{it}\beta^Q + FE_i + \varepsilon_{it} \qquad (1)$$

where *pit* is log price per seat for listing i and date t, F are controls for home and away teams performance, C are controls for competition from other similar listings, some of which are based on face value of the tickets. Q control for ticket characteristics and FE are game section fixed effects.

The author found evidence of declining prices as tickets sold nearer to the game day. Fixed price tickets price fell both in StubHub and eBay a month prior to game day. Individual sellers continue to cut auction start price through the week before the game. Prices were also declining even when the author use auction's closing price instead of starting price as dependent variable. Moreover, the author also found that probability of sales was increasing as prices were declining. This is consistent with standard dynamic model where sellers are moving along a stable residual demand curve since probability of sales may decrease if there were fall in demand or increase in competition. The

results are robust to changes in definition of dependent variables, fixed effects variables, also subsampling based on price distribution and attendance.

To prove the stability of the residual demand curve, the author run a probit regression of binary variable defining the success of an auction on its own starting price and several more listing characteristics variables. However, since starting price is endogenous the author used 3 other variables as instruments. Those variables are the distance from seller's zip code to home team's stadium, the proportions of seller's unsold listings that are relisted, and the proportions of seller's listings that are in fixed price or BIN formats. Estimating the models across four time periods; 1-10 days, 11-20 days, 21-40 days, 41 days and more; the author found that demand curves are very similar across those time periods. Hence, in conclusion, sellers are cutting price due to dynamic considerations rather than changes in demand or competition. This result is robust to changes in definition of dependent variables, control variables, and grouping of the instruments.

Noting the scarcity of articles on ticket resale, particularly empirical articles, Sweeting (2012) provides us with important knowledge. It used large datasets with both fixed price format and auction format. It also explained important variables affecting price besides the distance to the game day, such as seats quality. Moreover, it showed us alternatives of instruments for starting price in residual demand curve equation. The disadvantage of this article is it covers multiple topics and has numerous models that sometimes the definitions of some variables and econometric methods used are not very clear. Unlike Sweeting (2012) that focuses on the dynamic of ticket price, my study will be more focused on the general determinants of price, particularly the role of uncertainty in seat quality on ticket price determination.

Krueger and Pray (2008) tried to answer important questions that have been worrying many economists for a long time such as why does secondary market for concert tickets exist? Why do people buy tickets from secondary markets? Also, how big is this market? Many previous studies have tried to answer these questions and provided alternatives of theoretical explanations, however none of them use empirical survey data. Using survey data from 30 concerts in 2006 with addition of Bruce Springsteen's concert in 2002 and U2's concert in 2005 the authors found that the main reason cited for buying tickets in secondary market is to get better seats. Out of the tickets sold in primary markets, 10% of them are resold with average mark up between 45%-60%. Reselling rate is higher for higher quality seats and concerts that sold bigger proportion of tickets in the primary markets. Also, price tends to decline as we approach concert day and tends to be higher for tickets with higher primary market price. Ticket price in secondary market price is also affected by where the tickets are sold.

They argued that artists are constrained when determining their concert tickets by fairness as recognized by Kahneman, Knetsch and Thaler (1986) and Roth (2007). Artists do not want to be perceived as gouging their fans in order to gain long run loyalty and to build larger fanbase. Therefore, they are setting the price below short run profit maximizing level. This constraint, according to them leads to underpricing, which is more severe for the best seats. This argument is supported by one of their findings that best seats tickets are more likely to be sold.

Krueger and Pray (2008) collected data from Bruce Springsteen and U2 concerts constructed from a stratified random sample cluster of seats. Concert attendants are interviewed shortly before the start of the concert. There are 858 fans interviewed in Springsteen's concert and 903 in U2's concert. They also randomly selected 3 shows

per week with probability proportional to venue capacity from all concerts held between 6th of August 2006 until 27th of October 2006. Concertgoers in random sections of the venue are then interviewed for the study. They collected 3,281 interviews from 28 concerts. Sample size varies from 16 to 211 fans per concert.

They found that out of all survey respondents, 10% bought their tickets online. Average mark up rate is 36% for nation-wide survey. Also, in 2006, eBay and online brokers account to 20% of tickets sold in secondary market. Best seats tickets were tend to be resold more. They also resold for higher premium compared to the worst seats. Moreover concert tickets of superstars that tend to be sold out in primary market were also tend to be resold more and also at higher premium rate.

As for the reasons people go to secondary market, 51% respondents answered that they wanted to get better seats, the second reason is because tickets are sold out in Ticketmaster although it only accounts to 14% of the responds, only 11% stated the uncertainty of their ability in attending the concert as the reason why they bought tickets in secondary market. In addition to that, they also found that the respondents are exhibiting endowment effect phenomenon as more of them stated that they are willing to sell tickets for 300 US$ but only less proportion of them willing to buy tickets at the same price rate.

They reported that the distribution of secondary market ticket price is more dispersed and skewed to the right compared to the face value. As we are approaching concert date, ticket price is declining, however more tickets are being resold as the concert date were nearer. Also, StubHub mark up is the highest compared to other ticket selling sites, brokerages, and scalpers. The price in StubHub is 50%-65% higher than in eBay. They argued that this occurred because fans that bought from eBay were bearing

higher risk compared to StubHub buyers, therefore, they must pay lower price. Also, fans that bought tickets from secondary market spent more on merchandises and concession stands.

Although both authors do not employ much of an econometric model in the study, the survey study was very rare and difficult to be conducted. The questions in the survey are also useful in testing many theoretical works that had been done in this field. For example, the fact that tickets price are declining as we are approaching concert date and only small proportion of respondents stating schedule uncertainty as reason why they went to secondary market contradicted theoretical model in Courty(2003b). Some findings, such as how risk might affect price, endowment effect, and dynamic of ticket pricing are also valuable in motivating future works in this field.

3.3 Data and Hypotheses

3.3.1 Data Collection

The data for in this study were collected between July 16th 2012 and July 27th 2012 from Yahoo Japan Auction. In order to collect the data, the author first conducted a category search for auction ticket which is defined by the category menu Auction> Tickets, Voucher, and Hotel Booking> Box Office Ticket> Music> Japanese pop> Kanto. The result is a list of J-POP concert tickets that are sold in Kanto Area sorted according to auction ending time.

Everyday data on auctions that ended between 10 pm-12 am were collected. This time period was selected because that is the peak time when most auctions ended and trades took place. In addition to that, each day, data on auctions that ended on two additional hour period are also collected. This period changes everyday and it is

determined randomly. The complete schedule can be found in Table 3A-1. After the lists of auctions are saved, data are collected manually from each auction page. This approach were taken since the data on unsuccessful auctions are not available for sale and author were worried that excluding unsuccessful auction in the study might cause biased result on the effect of seat uncertainty on auction closing price. This might happen since certainty in seat quality might be correlated with auctions' success.

The data collected from each auction page consists of auction ID, seller ID, starting price/ minimum bid, Buy It Now Price, closing price, price cut indicator, number of bids, ending time, name of the concert, day of the concert, name of the artist, concert venue, indicator if tickets are sold in pairs, and indicator if seating arrangement is known or not. However, in order to conduct the analysis, there are some other information that might be needed, such as the face value of the tickets, the concert venues' capacity and type, and information on how the concert tickets are distributed. Those information are collected from the artists' websites, concert venues' website, ticket agencies' website, and several other sources. After dropping some observations where the information do not match and observations in which price is discriminated based on features of customers (tickets for mothers and schoolchildren), and further cleaning we ended up with 8,738 observations. The full list of the variables collected during data collection period is displayed in Table 3-1.

3.3.2 Descriptive Statistics

Table 3-2 depicts summary statistics of the main variables employed in this study. From the table we can see that 52% of auctions observed were *successful auctions*. The average closing price per ticket auctioned was about ￥11,700. However,

there was a big variation in the ticket's price across concerts and even in a concert. The distribution for *closing price* was skewed to the right that suggests that there were more expensive tickets auctioned than the cheaper one in this market. Besides rightly skewed, the distribution for closing price was also leptokurtic. The same phenomena can also be seen for variables *minimum bid*. When we divided these variables to face value of the tickets these features remain the same. We can see the distribution of these variables more clearly in Figure 3A-1.

Taking natural logarithm for *closing price* and *minimum bid*[12] reduce the skewness of both variables but the kurtosis is still quite high. There are some extreme values for *closing price* and *minimum bid*. Therefore, auctions with *closing price* above ￥100,000 are excluded from the model estimated in the next section. However, it does not cause a major change in the features of the distribution of those variables as we can see in Figure 3A-2.

Average *face value* is much lower than the average *closing price*. It is also lower than average *minimum bid*. This suggests that in general sellers' posted prices are in general higher than the one charged by official ticket sellers. In addition, it is also less skewed and leptokurtic. This fact combined with the previous findings might indicate that tickets auctioned in the secondary market have better seating arrangement and therefore more expensive, as reported by Krueger and Pray (2008) and Leslie and Sorensen (2013). However, different from all the previous studies, only 63% of the sample involves auctions for tickets with certain (known) seating arrangement.

[12] We defined *Lncp=Ln(closing price+1)* and *lnminbid=Ln(minbid+1)* and dropped observations in which closing price is higher than ￥100,000.

Out of all the auctions sampled, 7% of tickets auctioned were distributed in the primary market through *first come first served* method, 9% were distributed through *full lottery* method, and the rests were distributed by *lottery with general release* which is the most common method for selling tickets in Japan. Tickets were auctioned in this secondary market on average about 34 days before the concert date, however some of the tickets were auctioned more than 6 months before the concert. These particular tickets are usually tickets with uncertain seating arrangement.

In order to measure the *quality of the seating*, floor number is used in this study since the samples come from 526 different concerts with many varieties of seating format. The average floor number for the tickets auctioned in the observation period is 1.84, which roughly translates to the second floor in the venue. Also, the venues observed in this study range from one-floor venues to five-floors venue. Figure 3-1 describes the seat quality distributions of the tickets auctioned in detail. If we compare it with the median floor number for each venue, excluding tickets with uncertain seats, 22% of tickets sold were for seats located on better floor (nearer to the stage) than the median, 53% were for seats located on the median floor. The venues used for the concerts in our study vary from one-floor venues to five-floors venues. For example, Tokyo Dome is a four-floors venue. The proportion of uncertain tickets are higher is the venue gets larger and has more floors in general. Over 70% of the tickets sold are for a seat on first-level or second-level of the venue which is the nearest to the stage. Looking more closely based on the maximum level of the floors in venues, more than 70% of the tickets sold for the concert in two-floors venue in the auctions are for a seat in the first floor. More than 60% of the tickets sold for the concert in three-floors venue in the auctions are for a seat in the first floor or a seat on the second floor. Except for four-

floor levels venue, most tickets that were auctioned in secondary market are for a seat in the first floor or the second floor. This confirms the study done by Krueger and Pray (2008) that stated tickets sold in the secondary market are mostly tickets with good seating quality.

About 26% of the tickets were sold in pair. Sellers in the auctions we sampled have average *feedback rate* of 1522. Sellers' feedback score ranges from -1 to around 40,0000. For each auction, seller receives either one positive feedback or one negative feedback or zero feedback. A negative feedback reflects buyer dissatisfaction with the seller while a positive feedback reflects the opposite. Only two auctions in our observations involve sellers with negative feedback. These observations are dropped from our further analysis. There are 46 auctions where the sellers have zero feedback score. This usually occurs because the seller has never conducted an auction previously. The histogram of sellers' *feedback rate* can be found in Figure 3A-3. We can see that it is also skewed to the right and leptokurtic. Taking the natural logarithm[13] of the variable after dropping auctions with negative feedback makes the histogram looks closer to normal distribution.

Most of the observations, which is comprised of 97% of the auctions observed in this study, ended on the *peak time,* between 10pm-12am. Auctions ended in this period is oversampled since from the report provided by Aucfan[14] only about 69% of all the auctions in July 2012 ended in this period. This is due to the sampling method that sampled auctions ended in this period everyday in the observation period since most auctions are ended between 10pm-12am.

[13] We defined *lnfeedback=ln(feedback+1)* we also dropped auctions with negative feedback score and closing price higher than ￥100,000.
[14] Further break down of the distribution according to auctions' ending time can be found in Figure 2A-12.

Less than 1% of the auctions sampled had secret reservation price and only 33% had *buy it now* (BIN) option. Figure 3A-4 revealed that auctions with BIN option have lower success rate and average number of bids. It also has lower average *closing price* despite their higher *minimum bid* rate.

The average *venue capacity* of the concerts was about 16,000 people. On average the artists whose concert tickets were auctioned had been active for 10 years. Also, 81% of the tickets auctioned were for concerts in which the artists had recent hits while 27% were for concerts in which artists had a million selling album certification by RIAJ that can classify them as superstars.

Figure 3A-5 and Figure 3A-6 depicted the concerts features of the tickets auctioned during the observation period for this study. Out of over 526 concerts, 74% were not price discriminated. If ticket price was discriminated most only had 2 levels of price. About 61% of the concerts were held in venues that can hold 1000-10000 people. Over 95% of the concerts sampled were Jpop artists' concerts and over 38% of the concerts held were band's concert.

3.3.2.1 Statistics Grouped by Seat Certainty

Looking at seat certainty more closely, from Figure 3-2, we can see that on average, tickets with certain seating arrangement has higher success rate. Yet they yield less number of bids. Also, although the face value for those two types of tickets are only slightly different, auctions for tickets with certain seats have lower *minimum bid* and *minimum bid/face value* ratio. They also have considerably lower *closing price* and *closing price/face value* ratio, even for auctions where bids are positive. This might occur due to lower number of bids although we need to remember that many other

factors might change at the same time as seat certainty changes that might affect auctions' success and closing price.

Also, the figure includes all samples and some concerts contain tickets with certain seats only or uncertain seats only, therefore the previous conclusions are probably misleading. Limiting our sample to concerts in which seat certainty change from zero to one (from uncertain to certain) during our observation period resulted in the Figure 3-3 below. For this subsample, we can observe that auctions for tickets with certain seats have higher number of bids and success rate. Therefore fewer number of bids might not be the major factor causing lower minimum bid and closing price and their ratios to face value since they are still lower than the average minimum bid and closing price for the tickets with uncertain seats although the differences are not as big as before, especially for closing price.

Previously, we take simple averages of auction success and prices for ticket auctions regardless of the concerts. However, there are over 500 concerts included in our observations and they might be very different. Taking average success rate and average closing price for each concert and putting it against average seats certainty, we can see in Figure 3-4 and Figure 3-5 that the relationship of auction success and seat certainty is not clear. Whereas, higher certainty rate seems to coincides with slightly lower closing price for ticket auctions.

One of the possible explanations is that the average seat quality is worse for certain seat compared to the median level we assumed for uncertain seat. However, as explained previously, most of the tickets auctioned are tickets with good seat quality. This raised a question of why buyers bid for tickets with uncertain seat quality even more than for tickets with certain good quality.

However, there are many factors that we do not take into account here and the reason we will estimate some models in the next section. For example, tickets are perishable goods so that as we are nearing the day of the concert, price should go down and coincidently the seating arrangement only becomes known, as we are closer to the concert date.

3.3.2.2 Statistics Grouped by Days to Concert

Several previous studies have explored the relationship between *auction success/closing price* to *days to concert*. Dividing the *days to concert* into 4 quartiles and looking at its features in the Figure 3-6 we can observe that there are about the same number of tickets auctioned for concerts along the period with a little more tickets for concert with 0 to 19 days auctioned. In general, successful rate increases as days to concert is smaller with a little dip occurs for tickets for concerts take place in the next 11-19 days (Q2). However there is a considerable dip in number of bids for Q2 tickets.

While average minimum bid and average minimum bid/face value fall for tickets nearer the day of the concert, which confirms dynamic pricing theory for perishable goods as proven by Sweeting (2012), there is less clear pattern for average closing price and closing price/face value. The average minimum bid falls faster lower than face value as we are about 20 days from the concert date (Q2) and falls even lower as day of the concert gets nearer. Therefore, average minimum bid/face value falls even faster than minimum bid. The tickets price for concert tickets held in 20-37 days (Q3) is higher than for concert tickets held in 38-225 days (Q4) which is contrary to what predicted by dynamic pricing theory as stated by Sweeting (2012). Although it decreases for concert tickets in 11-19 days (Q2), closing prices and its ratio to face

value rises again for concerts tickets held in 0-10 days (Q1) from the day the auctions ended.

Taking average days to concert (from the day the auction ended) for each concert and plotting it against average minimum bid, successful rate, and closing price for each concert as depicted in Figure 3A-7 to Figure 3A-9 showed similar results. Average minimum bid falls as the days to the concert becomes smaller, the fall is steeper for concerts held around the next 40 days from auction date. Successful rate increases as we are nearing the day of the concert, which is also similar to the finding in Sweeting (2012) for MLB tickets. However there is less clear pattern for closing price in this study.

There are some possible explanations for this. Unlike in other countries, concert tickets selling in primary market are done in phases that involve lottery, general releases and revelation of seat quality as we go near the concert day. When people who failed to win tickets in primary market lottery flooded the secondary market to find tickets price should be driven up. General releases near the concert date supply the secondary market with more tickets. Also, as seating quality revealed, people who have good tickets might be tempted to sell their tickets for a good price and add more to tickets to the supply pool. People who have bad tickets might also sell their tickets and decided to buy tickets with better seat quality. All of these and maybe other factors make the dynamic of the closing price much more complex.

3.3.3 Testable Hypotheses

This study aims to find out the determinants of auction success and auction closing price (winning bid) for concert tickets in Japan. Numerous previous studies have

explored various determinants of auctions' properties, as explained in our literature reviews. However, none has examined the effect of quality certainty, in this case the certainty of seat quality in concert tickets auctions, on success and closing price.

People generally like certain things more compared to uncertain things. In addition, studies by Krueger and Pray (2008) and Leslie and Sorensen (2013) have shown that most buyers engage in trade in the secondary market in order to buy tickets for the best seats in the concert venue. Therefore, most concert fans are probably less interested in buying tickets with no seat information. This leads us to the first hypothesis:

Hypothesis 1. On average, auctions for concert tickets with certain (known) seat quality have higher probability of success compared to auctions for concert tickets without seating information, keeping other variables constant.

Following the same logic, despite lacks of evidence based on the descriptive statistics compiled in the previous section, fans are probably willing to pay less for tickets with no seating information. This leads us to the second hypothesis:

Hypothesis 2. On average, auctions for concert tickets with certain (known) seat quality have higher closing price compared to auctions for concert tickets without seating information, keeping other variables constant.

In addition, we also include various variables explored in previous studies as determinants of auction success and closing price.[15] Their expected effects on auction success and closing price are as follows:

Ln(minbid): we expect minimum bid set by sellers to have negative impact on success since it will be less attractive to bidders, however it will probably have positive impact

[15] The definition of the following variables can be found in Table 3-1

on closing price since the higher the starting bid, the higher the rest of the respective bids should be if there is a bid placed on the auction.

Excess: similar to the effect of ln(minbid), the higher the minimum bid (starting bid) compared to ticket's face value the lower success probability will be, yet it probably will yield higher closing price.

Relative Quality: higher seat quality is reflected by smaller relative quality since the floor number of the seats nearer to the stage is smaller compared to the seats/floor farther from the stage. Therefore, we expected relative quality to have negative impact both on success and closing price since fans will prefer to buy tickets with better seat quality and also will be willing to pay more for them.

Ln(compet): the more auctions for the same concerts offered at the same time on the auction web sites means that there are more competition in the market. Therefore, we expect that it will lead to lower success rate and closing price.

Paired: some auctions only offer tickets in pairs instead of individually, since it puts restrictions on the kind of bidders that can bid on this kind of auctions (e.g. only bidders who have a friend to go together to the concert can bid) we expect that it will have negative impact both on success and closing price.

Ln(feedback): feedback score is generally used as a measurement of seller's credibility. Sellers with higher feedback score are generally perceived as more credible. Also, there usually is lower risk of buying counterfeited tickets or of receiving bad services from these sellers. Thus, bidders usually feel more secure in buying tickets from these sellers and they are also willing to pay more. Therefore, we expect ln(feedback) to have positive impact on both success and closing price.

Ln(dtc): as observed by Sweeting (2012) and Krueger and Pray (2008), as the days of the concert draws nearer (days to concert becomes smaller), there are more trading activities. Thus, auction success should be higher. This probably should be more prevalent in this market since seating information is only released near the concert date. However, those studies found that the price of the tickets become cheaper near the day of the concert because seller can only sell the tickets until the concert date. Those tickets have no value after the concert takes place. Yet, in this particular market, seating information is only released near the concert date and the main reason why buyers engage in trade in secondary market is to buy tickets with high seat quality. Therefore, it might put upward pressure on closing price, unlike in previous studies.

BIN: as explored by Bhave and Budish (2014), auctions with Buy It Now option are less attractive to bidders, thus we expect that it will have negative impact on success. However, when there is a bid it generally they generally yield higher closing price.

3.4 Model Specification and Estimation Techniques

3.4.1 Modeling Factors Determining Auction Success

When concert tickets are auctioned, depends on various factors, buyers might buy it by placing a bid or they may not. If buyer decided to place a bid that is equal or higher than minimum bid and that bid is fulfilling some required conditions, e.g. higher than reserve price when one is placed, then the auction is considered to be successful. First, we will try to model what determines success in an auction particularly the effect of seat certainty on success. In the first model, continous variables are expressed in natural logarithm following the work of Dewan and Hsu (2004) and Lucking Reily et al.

(2007). We modified the model by adding variables unique to Japan concert ticket market.

$$\boldsymbol{successful_{it} = constant + seatcertainty_{it}\beta_1 + daystocon_{it}\beta_2 + X_{it}\beta^x + FE_i + \varepsilon_{it}}$$

where $successful_{it}$ is a dummy variable which has the value of 1 if auction is successful for concert *i* and auction *t*. X_{it} is the auction variables such as ln(minbid), ln(dtc), ln(feedback), day of the week the auction took place, time of the day the auction took place, and pair ticket dummy variable. FE_i is fixed effect used to control concert specific features such as whether the tickets distributed through lottery method in the primary market, capacity of the venue, the active year of the artist, hits, superstar, promoter, record company, and management company dummy, and concert type dummy such as band concert dummy, solo concert dummy, and festival dummy.

3.4.2 Modeling Factors Determining Final Price

Further, once bids are placed and buyers are bidding at various price level until an auction ended and we have a winner. We explore the factors affecting closing price, including the effect of seat certainty on closing price. We took similar approach with what we do in the previous section. In this model, we have natural logarithm of closing price (*lncp)* as dependent variable. We decided to transform closing price and several explanatory variables to their natural logarithm because the distribution of those variables in level[16] are skewed to the right, and leptokurtic. Therefore, the model is as follows:

[16] Dividing those variables with tickets' face value did not change the shape of the distribution either.

$$\boldsymbol{lncp_{it} = constant + seatcertainty_{it}\beta_1 + daystocon_{it}\beta_2 + X_{it}\beta^x + FE_i + \varepsilon_{it}}$$

$lncp_{it}$ is natural logarithm of closing price for concert *i* and auction *t*. X_{it} is the auction variables such as ln(minbid), ln(dtc), ln(feedback), day of the week the auction took place, time of the day the auction took place, and pair ticket dummy variable. FE_i is fixed effect used to control concert specific features such as whether the tickets distributed through lottery method in the primary market, capacity of the venue, the active year of the artist, hits, superstar, promoter, record company, and management company dummy, and concert type dummy such as band concert dummy, solo concert dummy, and festival dummy.

3.4.3 Estimation Techniques

3.4.3.1 Linear Panel Regression to Estimate Success and Final Price

The model to estimate auction success is supposed to be estimated using panel logit with fixed effects method or conditional logit method since the dependent variable is a binary variable. Concert is utilized as panel identifier in the estimations while each auction in each concert reflects an observation point. In order to take care unobserved heterogeneity that is not captured by all the independent variables, fixed effects approach should be employed to estimate the model. This is particularly important in this case since our sample comes from hundreds of concerts with very diverse characteristics. However, the marginal effects resulted from this method can only be acquired by assuming that fixed effects is zero. On the other hand, heterogeneity bias is probably a palpable problem in this study, given the characteristics of our data. Therefore, we chose not to use this method. As a result, we used Linear Panel Regression with Fixed Effects to run the model.

Similarly, Linear Panel Regression with Fixed Effects was employed to estimate the price model as well since tobit model with parametric conditional fixed effects model cannot be estimated, as there does not exist a sufficient statistic allowing the fixed effects to be conditioned out of the likelihood (Greene, 2002). However, using panel regression consequently means that only successful auctions can be included in the estimation since there is no closing price for auctions with zero bids.

Although we did not run panel logit with fixed effects method nor tobit model with parametric conditional fixed effects, we did employ Cragg's Double Hurdle Model taking into account the non-linear feature of the dependent variables.

3.4.3.2 Cragg's Double Hurdle Model

When modeling closing price of an auction, one of the most important features that needs to be considered is that closing price is not observed when auction is not successful. Thus, Tobit model with minimum bid as corner solution should be employed, However, there are some limitations to Tobit model. One of the key limitations is that in the Tobit regression the probability of a positive value and actual value, given it is positive, are determined by the same process. In this case the variables and parameters that determine success and closing price must be identical and have the same size and sign.

In general, double hurdle approach assures that individuals must pass two hurdles before being observed with positive level of closing price. Both hurdles are participation decision and bid decision. One of the most known double hurdle models is Cragg's model. This model allows both outcomes to be determined by separate processes (in this case success and closing price). It employs Probit model to determine

the probability of $y > 0$ and Truncated Normal Regression model given positive value of y. In STATA it run with *craggit* command.

Cragg's model is especially handy when we have many common variables that determine participation and the level model given participation. Contrary to this model, in selection model (e.g. Heckman selection model) exclusion restriction conditions must be met. That is, we need to find variables that affect participation but do not affect the level decision. Otherwise, it might lead to identification problem.

In this study, variables that affect success and closing price are very similar although they might not affect success and closing price in the same way. For example, higher minimum bid will drive buyers away from bidding at the auctioned tickets that lead to lower success rate. On the other hand, higher minimum bid will also made buyer bid higher price which will lead to higher closing price for an auction. Therefore, we chose to employ Cragg's Double Hurdle model in this study.

However, Cragg's Double Hurdle model does not allow panel data estimation option, which is the format of the data in this study. Therefore, unknown form of heterogeneity effect might not be captured. To reduce the bias we also include various concert specific features such as tickets distribution method in the primary market, capacity of the venue, the active year of the artist, hits, superstar, promoter, record company, and management company dummy, and concert type dummy variables as control variables and apply clustered standard error option. This is unlike what we did with panel data with fixed effects employed in the previous sections

3.4.4 Sample Restrictions

This study only uses concerts where seats change from uncertain to certain ($0 < mseat < 1$) during observation period since we want to particularly see the effect of seat certainty on success and closing price. The data used in the models are also restricted to sample with closing price less than 100000 since auctions with closing price higher than that are extremely rare and do not represent the market in general. Auctions for concerts in Tochigi are excluded since there is no successful auction there and so are auctions for concerts in Ibaraki. Across clusters, number of clusters varied greatly. Some clusters only have a single observation while some others have hundreds of observations with the maximum number of observations per cluster 453. In order to reduce some of the heterogeneity problems resulted from this occurrence we drop clusters that have less than 8 observations which is the first quartile statistic and retains 119 clusters and 4826 observations.

3.5 Results

3.5.1 Baseline Results

The baseline results of the regressions are presented in Table 3-3. The first column shows the effect of seat certainty and other variables on auction's success while the second column shows the determinants of auctions' closing price including seat certainty provided there is positive bid. Both are estimated using linear panel regression method with fixed effects. Column 3 also depicts the effect of seat certainty and other variables on auction's success while column 4 depicts the determinants of closing price, both using Cragg's double hurdle (Probit followed with Truncated Normal Regression).

Table 3-3 only contains variables of interest that will be discussed in this section, the full regressions result can be found in Table 3A-2 in the appendix.

The results show that seat certainty has positive and significant impact on the probability of auction's success as depicted in column 1 and 3. Linear panel regression with fixed effects results show that holding other variables constant, tickets with certain seats have 14% higher probability of successfully auctioned compared to uncertain. Probit results show that holding other variables at their means, tickets with certain seats have 18% higher probability of successfully auctioned compared to uncertain ones. These results indicate that ticket buyers generally prefer to buy tickets with known seating arrangement and less attracted to tickets auctioned without seating information. This results support Krueger and Pray (2008) and Leslie and Sorensen (2013) claim that fans mostly go to secondary market in order to get tickets with better seating arrangement.

Meanwhile, the impact of seat certainty on *ln(price)* show different results depending on the econometrics method used. Linear regression with fixed effects shows that tickets for certain tickets are on average generate 24% higher closing price compared to uncertain ones holding other variables constant and providing there is a successful auction. However Truncated Regression results show that there is no difference in closing price between certain tickets and uncertain ones. This result is not what the study expects since aversion to uncertainty in product quality should cause price to be higher for auctions for tickets with certain seat quality. Moreover, in concert tickets market, majority of the certain tickets sold have seat quality that are above the medium quality, therefore we expect seat certainty to have positive and significant

impact on *ln(price)*. However it should be noted that we did not control for heterogeneity across clusters when using Truncated Normal Regression.

After controlling for other variables, the regressions results show that days to concert has statistically significant impact on success when we employ linear regression with fixed effects yet it has no impact on *ln(price)*. Linear fixed effects regression result for success shows significant and negative impact. The negative and significant coefficients means the closer we are to concert day the greater probability of the auctions to be successful confirming Sweeting (2012). However, contrary to what is predicted by dynamic pricing theory of perishable goods, closing price does not fall here as we are nearing the day of the concert independent of econometrics approach employed. One of the reasons might be because, as Krueger and Pray (2008) mentioned, the main reason people go to resale market is to get better seats. Since seating only announced as we get nearer to the concert date, volume of transactions and number of bids were rising, preventing price from falling, as concert date gets closer. This might be made more severe by lottery method and phasing which made people who failed to win the tickets in each lottery session or phase in primary markets enter the secondary markets as the concert date gets nearer.

The signs and significance of other variables of interest are as expected and similar to the result of previous auction studies. *Ln(minbid)* has negative effect on success but the higher *Ln(minbid)* the higher closing price of an auction on average is. The same result is true for dummy variables indicating if minimum bid that is higher than face value of the concert tickets or equal to them. Estimates for relative seat quality suggest that he farther away the seat is from the stage (the lower the quality) the smaller is the probability of success and the closing price in auctions as expected. Tickets sold

in pair have significantly lower probability of success and lower closing price in an auction taking other variables constant.

Tickets auctioned under Buy It Now (BIN) option scheme has lower success rate compared to the ones without that option keeping other variables constant. However, the difference in *ln(price)* between tickets auctioned with BIN option and without the option given that auction is successful is not statistically significant at 5% level of significance. Meanwhile, the impact seller feedback on success show mixed results. The estimated impact on success is positive and statistically significant at 1% level of significance when we use linear panel regression with fixed effects, but it is not statistically significant at 1%, 5%, and 10% level of significance when we use probit but without panel fixed effect option.

Unlike what we expect previously, competition has no impact on neither auction success nor auction closing price. Also, we find that seller feedback has no impact on closing price at 5% significance level although it has positive and significant impact on success when we use linear panel regression with fixed effects. It seems that in this market, seat certainty affects bidders' behavior more strongly than sellers' credibility.

3.5.2 Discussion

The previous section indicates that tickets with certain seats information has higher auction success rate compared to the uncertain ones. Meanwhile, the impact of seat certainty on *ln(price)* are different, depending on the econometrics method used. In this section we will examine some of the reasons why these results might emerge.

3.5.2.1 Alternative Definition of Certainty

While we assume that tickets with uncertain seat quality have medium quality seating tickets and therefore identical within clusters, certain tickets vary in quality. Although we already controlled for relative seat quality, we did not differentiate them based on seat certainty. In this section, we divide certain tickets into three categories:

1. *Good* when the floor where the seat located according to the ticket is nearer to the stage compared to the medium floor of the concert venue.
2. *Medium* when the floor where the seat located according to the ticket is on the medium floor of the concert venue.
3. *Bad* when the floor where the seat located according to the ticket is farther away from the stage compared to the medium floor of the concert venue.

The estimates from the regressions for these variables and relative seat quality variable are presented in Table 3-4. These results show that there is no difference in probability of auction success and in *ln(price)* between certain tickets with bad seat quality and tickets with uncertain seats quality irrespective of econometrics methods. On the contrary, on average and keeping other variables constant, tickets with good certain seat quality and tickets with medium certain seat quality have higher probability to be auctioned off successfully compared to tickets with uncertain seats quality. However, similar as in the previous section, based on linear regression with fixed effects, tickets with good certain seat quality and tickets with medium seat quality have higher closing price compared to tickets with uncertain seats quality. Yet, we could not find any statistically significant difference in its impact on closing price between those tickets and tickets with uncertain seats quality based on Truncated Regressions results.

In addition, we also found some changes in the statistical significance and the size of the estimates of relative seating quality when we redefine seats certainty. This

result is produced probably because the new definition is a mix between seat certainty and seat quality. Now, the estimates for the impacts of relative seat quality on auctions success become not statistically significant. While the estimates for the impact of relative seat quality on *ln(price)* are still negative and significant at 1% significance level, the size are a little smaller compared to the results in the previous section.

3.5.2.2 Top Concerts

One of the concerns in this study is the heterogeneity of the sample. The data collected for regressions analysis includes 119 different concerts. Some have very few observations while some have more than 300 observations. Some concerts were held in big venues with capacity of 50.000 people whereas some concerts were held in small venues with capacity of less than 500 people. In order to curb the heterogeneity bias, especially when we use Truncated Regressions, we will limit our samples to concerts with top traded tickets in this section. We define top traded concerts as concerts that have more than 10 observations included in our observations period. In the end, we ended up with 47 concerts. These concerts mostly held in large venues with only one concert held in a venue with capacity less than 2000 people. However, the concert dates vary greatly across concerts. Some concerts are held even within observations period while some other are held about five to six months after the observation period.

From the results in Table 3-5 we can see that for top traded concert, not only that seat certainty has a positive and significant impact on auctions' success, but it also has the same impact on *Ln(price)* at 1% level of significance taking other variables constant. In this case, certainty in quality of the seating not only affects buyers' decision to bid but also their willingness to pay. This result confirms the findings of other previous

studies concerning uncertainty in product quality. This result might emerge because the buyers in secondary markets for these top concerts might come from wider general public compared to other concerts, therefore they consists of not only die hard fans and as a result are more risk averse. However, it might also due to the fact that we have more observations per concert in this setting, which enables us to have more information and more efficient results.

Paired tickets still have lower probability to be successfully sold in an auction and lower closing price as well in general. Meanwhile, the higher *Ln(feedback)* for seller, the higher also the probability of their tickets to be successfully sold in an auction. This result seems to be in line with the argument that buyers of top concerts tend to be more risk averse. On the other hand, the higher *Ln(feedback)* the lower the closing price it generated in an auction. This probably is due to the pricing strategy of seller with higher feedback, which is usually also more experienced seller. In accordance with the baseline results, the day of the concert has no impact on probability of success and on the closing price of a ticket auctioned at 5% significance level. Therefore, we cannot confirm dynamic pricing theory as found by Sweeting (2012).

3.5.2.3 Addition of Groups Average to Cragg's Double Hurdle Results

One other effort to limit heterogeneity bias when we are using Truncated Regressions is by adding cluster averages of the covariates into the regressions similar to Mundlak (1978) correction.[17] The comparisons between the estimates computed without cluster averages (baseline) and estimates computed with cluster averages are

[17] This is done by assuming that the relationship between $X_{is}$and $\varepsilon_i$can be written as $\varepsilon_i = \bar{X}_i\alpha + v_i$ where v_i is iid ~ follows the normal distribution and is independent of X_{is} and $\boldsymbol{\epsilon_{is}}$ for all i and s. In practice Mundlak corrections can be applied by including the artist average (across GCA) for each of the GCA varying explanatory variables in the right-hand side of Equation 2.

presented in Table 3-6.

In contrast with the baseline results, the results suggest that seat certainty has a positive and significant impact on both auctions' success and *Ln(price)* at 1% level of significance taking other variables constant when we add cluster averages as explanatory variables in the Truncated Regressions. In addition, using more specific definition of certain seats, the results show that tickets with certain seat quality have higher probability of auction success compared to tickets with uncertain seats. It does not matter if seat quality is good, medium, and bad seats. Tickets with good and medium seat quality generate higher closing price than tickets with uncertain seats. However, there is no statistical difference between the closing price of auctioned tickets with uncertain seat quality and auctioned tickets with bad seating quality. This result is similar to the results of linear panel regression with fixed effects.

3.5.2.4 Other Model Alterations

3.5.2.4.1 Days To Concert

Previous results show that natural logarithm of days to concert *ln(dtc*) only affects success when linear panel regression method was employed. Also, we did not find any evidence that *ln(dtc*) affected auctions' closing price. Our results did not suggest that there was evidence of dynamic pricing in this market. This result is different from what reported by Sweeting (2012). However, this market is different from Secondary Market for MLB games tickets that was observed by Sweeting (2012) in several ways. In this market, seat arrangement is normally announced, as concert date gets nearer. Tickets with certain seat quality become available in the secondary market after the announcement. As a result, the trading activity in resale market picks up a

couple of week before the concert date. This will probably affect price in different way from what predicted by dynamic pricing theory for perishable goods. However, as mentioned previously, concerts included in our samples are very diverse with varying concert dates. Some of the concerts have distant concert dates while others have very close concert dates during our observation period. In order to see these things that occur near the concert date more closely, we are dropping ticket auctions for concerts that took place after August 5th 2012, which is about a week after the observation period. In addition, we are also replacing days to concert variables with a set of dummy variables *dtth1-dtth5* that indicate whether the tickets were auctioned one to three days before the concerts, 4-6 days ahead of the concerts, 7-9 days ahead of the concerts, and so on until 15 days ahead of the concert dates.[18]

The results presented in Table 3-7 suggest the introduction of these dummy variables and the elimination of some of our observations do not change the results of the model estimations in general. Similar with the baseline results, seat certainty has positive and significant impact on success at 1% significance level, yet it does not significantly affect *Ln(price)* most of the time. The results show that tickets auctioned 1-3 days, and 4-6 days before their concert date have higher probability of successfully sold in auction compared to tickets auctioned for concerts that occur in 7 days or more. Meanwhile, only tickets sold 4-6 days before their concert dates tend to end up with significantly lower closing price taking other variables constant compared to tickets auctioned for concerts that occur in 1-3 days or at later dates. This is probably due to the deadline for ticket sellers that are only allowed to sell tickets up to 3 to 4 days before the concert date in other secondary marketplaces (ticket.co.jp, ticketstreet, ticketcamp).

[18] The base in this case is dtth6 that indicates auction occurs 16 days before the concert date or more.

This might cause the number of tickets sold to increase in Yahoo Japan Auction and closing price to fall.

3.5.2.4.2 Seat Quality Announcement

Before seating detail is announced, there should only be tickets with uncertain seat quality available in the secondary market. Only after seating arrangement is announced do tickets with certain quality become available for auctions in the secondary markets. Figure 3-6 displayed the evolution of daily concert average of number of auctions, seat certainty, auctions' success, and normalized closing price from three days before seat announcement until three days after seat announcement for top traded concerts.

From Figure 3-6 we can see that there were some changes occurring around the time when seat quality was announced. First, number of tickets being auctioned increased greatly after the announcement and peaked one day after the announcement. There was a slight increase in average success and we can see that it has taken a dip one day before the announcement. As day of the announcement drawing near, not many sellers sold their tickets and buyers were also waiting for the announcement to bid for tickets. Normalized price decreased a little after the announcement, although it must be noted that tickets' price should decline, as concert day gets nearer if tickets are not sold out. Average certainty did not increase immediately to one as seat arrangement announced but more and more tickets with certain quality became available in the market. Table 3A-5 shows the detailed tabulation of tickets sold before and after announcement and the seat certainty. It showed that although there are some tickets with certain quality sold before announcement, the number was very small. Meanwhile,

there were indeed considerable numbers of tickets with uncertain seat quality sold after seat announcement. This is possible because sellers are probably late in updating the seat arrangement for few days, for example because they didn't receive the post on the announcement day for some reasons. This seems to be the main reason since the numbers of seats with uncertain seat decrease substantially three days after the announcement. Nevertheless, there were still seats with uncertain quality sold afterwards. In this case, sellers were relisting tickets with uncertain seat quality and did not update the information because of some other reason. They either did not care to update or did not want to update because the qualities of the seat for those tickets are not good or some other unknown reason.

If we expand the observations and see how those indicators are behaving around concert date we end up with Figure 3-7. Average certainty was one or very near to one near the time of concert date, which means only tickets with certain quality auctioned near the time of concert date although there were still some tickets with uncertain quality auctioned after seating quality was announced. Average number of auctions was not as high as after seat announcement and plunged three days before the concert although it slightly increased one day before the concert date. Average success was generally higher near concert time compared to before seat announcement. Normalized closing price decreased more compared to few days after seat announcement although it climbed up again starting from three days before the concert. This might be due to last minute selling and buying of fans that have schedule problem instead of professional traders indicated by lower number of tickets sold by sellers during observation period. Krueger and Pray (2008) detected endowment effect among fans that engage in ticket

trading in secondary market. This effect might be the reason why price was high and was not much different from the level around seating announcement time.

Since tickets with uncertain seat quality before seat quality announcement must be different from the same kind of tickets after announcement, its effect on auctions' outcomes are probably different as well. Lastly, we also run the equations including pre-announcement dummy as one of the control variables for top traded concerts. The results are depicted in Table 3-8. There is no major difference in the estimates compared to the results for top traded concerts without pre-announcement variable. Seat certainty is still positive and significant in all equations. However, the estimated effect of seat certainty on *ln(price)* are now slightly lower. Nevertheless the estimates for seat certainty are now slightly different. Instead of measuring the difference in the success and *ln(price)* between tickets with certain quality and uncertain quality, they now measure the difference in the success and *ln(price)* between tickets with certain quality and uncertain quality given they are auctioned after the seats quality are announced. The estimates Pre-announcement dummy on the other hand measure the difference the success and *ln(price)* between tickets with uncertain quality before and after seat quality announcement. It has negative and significant estimates in *ln(price)* equations.[19] This suggests no difference in the probability of success for uncertain tickets before and after seating announcement. However uncertain tickets auctioned before the seating announcement generate significantly lower closing price compared to uncertain tickets auctioned after the announcement, keeping all other variables including seat certainty and seat quality constant.

[19] We exclude 93 auctions out of 8740 observations with certain seats before seat quality announcement since it might be due to mistakes or ticket fraud.

Redefining tickets with certain seat quality into *Good, Bad,* and *Medium* category does not change the results much. The results depicted in Table 3-9 shows the pre-announcement estimates are almost exactly the same as in Table 3-8. The signs and the significance of estimates for variable Relative Quality do not change either although they are now smaller in size. In addition, the results show that auctions for tickets with *Good* and *Medium* seat quality have higher probability of success and higher *ln(price)* in general compared to auctions for tickets without seating information that were auctioned off after the announcement made. However, auctions for tickets with *Bad* seat quality have higher probability of success and higher *ln(price)* compared to auctions for tickets without seating information that were auctioned off after the announcement only in the cases where we omitted fixed effects.

3.6 Conclusions

The way concerts tickets are usually sold in the Japanese primary concerts tickets markets cause concerts tickets to be sold without information of the quality of the seating for some periods of time in the secondary markets. This study seeks to understand the determinants of auctions' outcomes: success and closing price in this unique environment. In particular, how certainty in seat quality affects auctions` success and closing price as opposed to uncertain seat quality. Using secondary markets data from Yahoo Japan Auction we found that tickets auctioned with certain seat quality have higher probability of success, this result is robust to changes in econometrics methods, control variables, and samples. While the evidence for the effect of seat certainty on auctions' closing price is less clear, we found that for top traded concerts, tickets with certain seat quality tends to generate higher closing price taking all other

control variables as given. We also found similar result when we control heterogeneity by adding cluster averages in the regression.

Similar to seat certainty, in most cases as day of concert draws nearer the probability of a concert ticket successfully sold in an auction rises. However, just like in seat certainty case, it is harder to find evidence that days to concert affects Ln(closing price). Finally, introducing pre-announcement variable to the equations show that tickets with uncertain seat quality sold before seat quality announcement have lower closing price compared to uncertain tickets auctioned after the announcement, while we found no difference in success rate between them. In addition, tickets auctioned with certain quality after seats quality are announced have higher success rate and ln(price) compared with those with uncertain quality.

CHAPTER 4 MISSED OPPORTUNITIES IN COMPETING ONLINE AUCTIONS: A STUDY OF JAPANESE CONCERT TICKETS AUCTIONS

4.1 Introduction

Widespread internet access and advances in technology have led to the emergence of online auctions as a popular platform to trade goods and services. While the study of auctions has been the emphasis of a growing literature in economics field, standard auction theory typically assumes that auctions are independent of one another. Whereas in many online auctions competing sellers usually auction a number of substitutable goods simultaneously. As a result, buyers have opportunity to choose among many auctions and there is an interdependency of auctions' outcomes.

In the competing auctions environment, the rational way for a bidder to play is not completely clear, but a natural and simple rule is to bid on the auction with the current lowest price. Peters and Severinov (2006) for instance show that following this rule and raising bids as slowly as is possible, yields a perfect Bayesian equilibrium in the bidding process independently of a bidder's beliefs about other bidders 'valuations and the number of other bidders. An implication of following this strategy is that when the auctions end, the reservation prices of any unsold items should be above the winning bids on sold items. A failure of this property would mean that at least one person had placed a bid above that required to be a winning bidder at some stage in the auction. This failure would imply that at least a buyer made a mistake. However, while majority of references in competing auctions assume that goods auctioned are identical,

in real life setting goods are generally substitutable or similar but not identical.[20] Goods might be a bit different in terms of the quality or certainty but highly substitutable. In other setting, goods auctioned might be the same, but the sellers are different. Those differences might affect bidders decision. Therefore, we choose to be more careful and use the term 'missed opportunity' instead of mistake to describe the failure, and examine the effect of those differences in this study.

In this study, we examine whether bidders create 'missed opportunities' in their bidding strategy by not bidding on the auction with the lowest standing bid. We are specifically interested in competing auction groups in which there is at least one unsuccessful auction (auction that receives no bids) with lower reservation price compared with closing price of all successful auctions in the competing group, by the time the auctions end. We also explore the size of the 'missed opportunities' when it occurs and variables affecting both the occurrence and the size of it.

The data analyzed in this paper consist of online auctions for concert tickets at Yahoo Japan Auction. While highly substitutable, concerts tickets are usually differentiated in terms of seat quality printed on the ticket. Nonetheless, there are periods of time that all tickets for a concert are auctioned in the market without seating quality information making the goods more alike as a consequence of the unique feature of Japanese concert tickets market. This paper will also investigate the effect of this feature on bidders decision.

To preview our results, we find that 'missed opportunities' are common and often quite large compared to the face value of the tickets or the reservation price.

[20] Several references in competing auctions with identical goods are McAfee (1993), Peters and Severinov (2006), and Gerding et al. (2008).

While we cannot rule out the possibility that the results are due to subtle differences in the features of tickets and sellers reputations that were, our results seem to be robust and missed opportunity still occurred even when we confined the analysis to the most homogeneous groups of tickets.

The rest of the paper is organized as follows. Section 2 presents prior related literature on competing auctions. Section 3 describes the institutional features of Japanese concert market and Yahoo Japan Auction as well as the dataset we use. We will explore the research methodologies in section 4 and present the results in section 5. Section 6 will discuss our results and Section 7 will conclude our study.

4.2 Literature Reviews

One of the earliest studies on the theory of competing auctions was done by Engelbrecht-Wiggans and Weber (1979). They analyze a multi single unit auction environment with identical goods motivated by the example of dressers as the goods and husband-wife couples as potential bidders. Couples can choose to go to one seller together or to separate and participate in two auctions with a risk buying more than one dresser. They derived mixed Nash equilibrium strategy that requires randomization. They also argued that when identical goods are sold in simultaneous independent auctions, those auctions should not be treated as independent auctions since there is a possibility that individuals might bid differently in different auctions depending on their capacity and budget constraints, and other non-linearity in their utility functions.

Subsequently, more papers concerning competing auctions were written. McAfee (1993) assumed that sellers held identical auctions then buyers randomized among sellers in the market. Peters and Severinov (1997) extended that model by

exploring the case when seller changes strategy and deviates. However, since both assumed that the only equilibrium involves bidders who randomize among available sellers to buy from one seller, it is a possibility that some auctions have many bids and bidders when some have none. This way, some of profitable trades might not be realized.

This empirical study is partly prompted by theoretical predictions formulated by Peters and Severinov (2006). They studied simultaneous ascending second price auctions where sellers sell a single unit homogeneous good and set reservation prices at their own second-price auctions. Buyers have a private value for the good and wish to acquire a single unit and can bid as often as they like with no cost and move between auctions. Sellers simultaneously announce reservation prices in their auctions then buyers arrive sequentially. In this environment, they propose that the strategy that buyers use to select among sellers' auctions requires a buyer to bid at an auction with the lowest current price and raise his bid as slowly as possible (as long as the bid is below his valuation). The only two pieces of information that a bidder needs are the standing bid, i.e. the current price in the auction, and whether the standing bid has changed since the last change of the winning bidder which is not unlike the environment traders face in online auctions sites like eBay or Amazon. They also implied that bidders adopt cross-bidding strategy in order to apply this strategy.

Anwar et al. (2006) investigated the theory proposed by Peters and Severinov (2006) using competing auctions for CPUs on eBay that took place during the period January 26 2002 – May 18 2002. They considered CPUs auctions as competing auctions if the goods are single items that are homogenous in quality, have similar methods of delivery and shipping costs, auctions run by the same sellers, and end at approximately

the same time (they divided their groups into auctions that end within the same day, within an hour, and within a minute of each other). Although they reported that only 14%-20% of the bidders are cross-bidders, bidders do tend to bid on auctions with the lowest standing bid-62% for the daily sample, 72% for the hourly sample, and 76% for the minute sample. These proportion are statistically different from 30%-50% for random bidding. They also found that winners who cross-bid pay significantly less than those who do not.

Hoppe (2008) conducted an experiment of parallel multiple auctions with homogenous goods. Auctions conducted for 15 rounds each session and there are 7 sessions in total. There are 3 sellers and 4 bidders in each round. Sellers and buyers were provided with same endowment and assigned private valuation from a uniform distribution. Sellers can set their own starting bid and bidders receive information on starting price, standing/current price, and second highest bid history since the auction format is second price auction with hard close ending rule. He found that the frequency of unsuccessful auctions increase with number of rounds (the mean is between 15%-25%) with the exception of the auctions with the lowest starting bid that has zero unsuccessful auction except in one round. He reported that the proportion of cross-bidders is about 20%-25% on average and about 60% of the bidders are single auction bidders. He also found sign of coordination failure[21] and sniping[22]. Further empirical work inspired by the theoretical predictions of Peters and Severinov (2006) was conducted by Kayhan et al. (2010). Using data from eBay auctions of Apple iPod players, they defined simultaneous auctions as auctions of similar goods that end within

[21] Failure among bidders to coordinate which results in two or more bidders with high valuation to place bids on the same auctions. On the other hand, if they were able to coordinate and bid on different auctions they would win and increase social welfare.

[22] The practice of submitting bid as late as possible in the auction (late bidding).

10 minutes from each other. They found that only 15% of bidders engaged in cross-bidding activity and only 5% of them won the auctions. However, cross-bidders winners did enjoy price discounts compared to non-cross bidders although the size of the discounts are not large ($2.5-$3.5 for players with closing price around $81.51-$324.70). They also found that more expensive products, higher number of simultaneous auctions available, and higher number of experienced bidders led to more cross-bidding activity.

While other previous literatures focus on environment where goods are identical, Bapna et al. (2010) examined the case where sellers offered vertically differentiated goods in simultaneous Vickrey auctions. They proposed a theoretical model for imperfect substitute auctions then conducted a controlled experiment with identical goods but varied sellers reputation to observe whether bidders risk attitude alters their theoretical results. Auctions are ranked according to their relative attractiveness (product quality, value certainty, and seller reputation) and bidders self select into a finite number of zones depending their private valuations. When bidders are assumed to be able to submit only one bid, bidders whose type fall into the highest zone always bid on the highest auction, buyers whose type fall into the second highest zones randomize between the second highest auctions and the highest ones assigning higher probability of bidding the second highest auctions, and so on similar to *probabilistic positive assortative matching*. When bidders can submit more than one bid, equilibrium strategy for bidders is to place non-zero bid to all auctions although bidders have a unit demand. The optimal bid amount is equal to bidders expected valuation of respective auction and the probability of bidders not winning an item from their other bids given their other bids. Consequently, low type bidders tend to place equally serious bid on all auctions while high type bidders tend to focus more on fewer and generally higher zone auctions.

The experiment showed that bidders with the highest valuation are more likely to bid on highest reputation seller. When valuation decreases, likelihood to place more bids increases as well as probability to bid on lower reputation sellers. This result is moderated by the effect of risk attitude as risk tolerant bidders tend to place more bids and more likely to place a bid on low reputation sellers. When bidder only place one bid (57% of the bidders), they put disproportionately higher probability to choose to bid on auction of highest reputation seller. They conclude that simultaneous auctions suffer from coordination failure, which leads to low allocative efficiency. However, they did not examine the effect of starting bid since starting bid is zero in all settings.

While there are several empirical literatures on competing auctions, all of them are focus on cross-bidding. This study, offer a new perspectives on examining competing auctions. We also look more carefully on the effect of slight heterogeneity, which is a common feature of online auction market.

4.3 Institutional Features and Data

4.3.1 Institutional Features

4.3.1.1 Features of Japan Concert Industry

The Japanese concert industry possesses several unique features that sets it apart from concert industries in other countries. One of its characteristics that might affect this study is that generally promoters and ticket agencies sell tickets without seating information. Ticket buyers cannot choose where they sit and only discover the seating details when promoters and ticket agencies send them the tickets or send them an e-mail to print the tickets few days before the concert date. As a result, tickets are auctioned for sale without seating information in Yahoo Japan Auction for some period of time,

making the goods' quality more homogenous. Although many of the tickets are almost identical, nevertheless in some cases small differences between products persist e.g. some tickets are sold in pairs while others sold individually, some tickets are sold with Buy It Now options and some others are not, also seller reputation are different across auctions. More importantly, there are some markets, particularly close to the concert date, where seating information is available in some form.

4.3.1.2 Features of Yahoo Ticket Auction

Yahoo Japan Auction is the biggest online auction market in Japan. This auction site shares many similarities with eBay, which is the site that is described in most theoretical and empirical studies. However, there are also some notable differences between the two online auction sites.

First, Yahoo Japan Auction allows sellers to extend the auction's ending time for 5 minutes if at least one bid is submitted in the final 5 minutes before the auction ends. This way, bidders always have opportunities to submit bids after observing other buyers' bids. Consequently, there should be less incentive for sniping and overbidding. Furthermore, unlike in eBay, Buy It Now (BIN) does not vanish although the auction has received a bid as long as the bids are not equal or higher than the Buy It Now (BIN) price.

Despite their differences, other auctions features are similar in these two auction sites. Both sites allow proxy bidding and have bid increment rules. They also have feedback scoring system that allows bidders and sellers to learn about each other's reputation.

4.3.2 Data Collection and Auction Group Formation

4.3.2.1 Data Collection

The sample used in this study consists of concert ticket auctions of J-POP artists collected between July 16th 2012 and July 27th 2012 from Yahoo Japan Auction. As the first step to collect the data, we first conducted a category search for auction ticket which is defined by the category menu Auction> Tickets, Voucher, and Hotel Booking> Box Office Ticket> Music> Japanese pop> Kanto. The result is a list of J-POP concert tickets that are sold in Kanto Area sorted according to auction ending time.

Everyday data on auctions that ended between 10 pm-12 am are collected. This time period was selected because that is the peak time when most auctions ended and trades take place.[23] In addition to that, each day, data on auctions that ended on two additional hour period are also collected. This period changes everyday and it is determined randomly. The complete schedule can be found in Table1 Appendix B. After the lists of auctions are saved, data are collected manually from each auction page. This approach was taken since the data on unsuccessful auctions are not available for sale. Thus, we are worried that excluding unsuccessful auction in the study might cause biased results since certainty in seat quality might be correlated with auctions' success. After dropping some observations where the information do not match and observations in which price is discriminated based on features of customers (e.g. tickets for mothers and schoolchildren), we ended up with 8738 observations.

We observed several auctions with secret reserved price and dropped 16 observations from the dataset. Further 33 observations dropped since the auctions listed some more specific bidder restrictions. Finally we also dropped 284 auctions occurring

[23] Auctions during that period accounts to 70% of total daily auctions and 72% of daily successful auctions.

outside the two hours window between 10 pm- 12 am. We ended up with 8409 observations.

4.3.2.2 Auction Groups Formation

Auctions belong to the same group of competing auction (GCA) in our data set if they satisfy the following conditions. First, they are ticket auctions for the same artist. Second, they are also ticket auctions for the same concert day since one artist may have several concerts planned. Third, tickets auctioned are of the same seat certainty value. Therefore, GCAs are consisting of either only ticket auctions without seating information or only tickets auctions with some form of seat information. Fourth, tickets auctioned are for the same floor within the concert venue. Also, some concerts tickets are auctioned in pairs, which is not unusual since people frequently go to concert with their friends. Thus, within GCAs auctions are restricted to be either only for paired tickets or only for non-paired tickets. Sixth, they also have the same option regarding Buy It Now Option. Thus, GCAs are consisting of either only auctions with Buy It Now option or only auctions without Buy It Now option. Lastly, they end at approximately the same time, which is within 2 hours window (10pm to 12 am) from each other on the same auction day. Figure 4-1 depicts these similar features of auctions within GCA.

Within GCA, tickets auctioned are for the same artist and concert. However across GCA the sample consists of 289 artists and 370 different concerts across groups. It also should be noted that in previous studies (Anwar et al., 2006; Kayhan et al., 2010), goods auctioned were limited to single unit auction as assumed in Peters and Severinov (2006). We did not restrict our sample to only single unit ticket auction. Nevertheless, because it is impossible for someone to be at the same concert twice simultaneously, the existence of multiple unit demand bidders might not be as serious as in previous cases.

The starting and ending times of auctions in this study are not the same. However as stated by Anwar et al. (2006), auctions that end at approximately the same time compete more directly against one another compared to those that end at considerable different ending times. Also, sellers are different within GCA in this study.

As mentioned earlier, tickets auctioned within a GCA are for the same concert and the same artist, and the same value certainty. Therefore, they are highly substitutable albeit having some differences. However, value certainty is different across GCA since although for some period of time tickets are auctioned without seating information, there are also tickets sold with seating information in some markets. In these markets, tickets quality is heterogeneous because the seats printed on the tickets are different. Some of them are probably for seats near the stage and others are for seats at the back of the venue. Thus, we restrict auctions within GCA to be for auctions for the same floor to limit the heterogeneity. There are still slight differences in seat quality within those GCAs since tickets can be for seat on different rows and seat numbers within a floor.[24]

Based on all the information above, we divided our data set into 3 categories, the entire dataset and 2 subsamples. The first is the entire dataset (the 'All' column) that includes the groups of competing auctions for both tickets with certain seat and groups with uncertain seat. The second ('Uncertain') is a subset that only consists of groups of competing auctions for tickets with uncertain seat at the time of auction. The third ('AKB48') is a subset of the uncertain groups of competing auctions that consists of

[24] We were not able to isolate these differences within GCA since we will lose majority of our sample. However we later ran regressions of missed opportunity and its size against seat quality heterogeneity for only GCAs with seating information and this level of seat quality heterogeneity are not significant in most of the specifications.

groups of competing auctions for AKB48[25] concerts. This subsample is the largest subset for a single group and is selected for that reason. Auctions appearing in the AKB48 subsample also appear in uncertain subsample and in complete data. Each group of competing auctions in these three categories consists of two or more auctions.

Table 4-1 provides the summary of our data. We only consider group of competing auctions where there is a variation in auctions success. We only consider these groups because when all goods are sold or unsold it is not possible to conclude that there is sub-optimal bidding behavior, as we do not have bidding time information. As expected, overall sample has the largest number of groups and observations (auctions), followed by uncertain seat sample, and AKB48. However, the average number of auctions per group is not very different, as a matter of fact AKB48 subsample has the largest average number of auctions per group while overall sample has the smallest number. The opposite is true for the standard deviation suggesting that as we go from overall sample to AKB48, the size of the group generally gets bigger while the size of the group for overall sample is more varied. Furthermore, average number of bids for AKB48 subsample is also the largest, followed by uncertain seat sample, then overall sample. This might suggest that compared to uncertain seat subsample and overall sample, AKB48 subsample groups have the most supply and demand and it is the same if we are to compare uncertain seat subsample and overall sample.

[25] We intend to look more closely at this subsample because it contains the biggest number of observations and it allows us to investigate the research questions in more homogeneous environment.

4.4 Variables Definition and Research Methodology

4.4.1 Variables Definition

Suppose there are N competing auctions in a group. Let R = set of reservation prices on unsold tickets and let M = set of winning bids on successful auctions.

Define $\mathrm{D} = \{\mathrm{m} - \mathrm{r} | \mathrm{m} \in \mathrm{M}, \mathrm{r} \in \mathrm{N}, \mathrm{m} - \mathrm{r} > 0\}$

We use the term 'missed opportunity' for any outcome in which at least one competing auction was unsold and at the same time, at least one winning bid was greater than the reservation price of the unsold ticket. In other words, there is no missed opportunity $D = \varnothing$. This is an ex-post definition of missed opportunity. There are a number of ways of measuring the scale of the missed opportunity. We define

4.4.1.1 Error Measurements

1. ***errormax*** $= \arg\max_{d \in D} d$ = the difference (in yen) between the largest winning bid and the smallest reservation price on unsold tickets in each group. The value lies between 0 to any positive number (bound to zero if it is negative). The value is identical for all observations (auctions) in GCA.
2. ***errormin*** $= \arg\min_{d \in D} d$ = difference (in yen) between the smallest winning bid that exceeds a reservation price on an unsold ticket and the highest reservation price that is below that winning bid. The value lies between 0 to any positive number (bound to zero if it is negative). The value is identical for all observations (auctions) in GCA.

Errormax covers the whole range of the errors in the GCA. However, it is sensitive to outliers such very high winning bid and very low reservation price. *Errormin* is a narrower and more conservative normalization of errors. It is less affected by outliers except when numer of auctions is small. However, it does not contain all the range of errors and might not fully capture errors' features within GCA. Therefore, *errormax* is the loosest definition of error while *errormin* is the strictest definition of error.

4.4.1.2 Missed Opportunity Measurements

There are two variables that we use to measure missed opportunity:

1. ***missopmax***: a binary variable that is equal to 1 if *errormax*>0 and equal to 0 otherwise. The value is identical for all observations (auctions) in the same GCA. When it is equal to 1, it means at least one winner has erred (probably made mistake).
2. ***missedop***: a binary variable that is equal to 1 if *errormin*>0 and is equal to 0 otherwise. The value is identical for all observations (auctions) in the same GCA. When it is equal to 1, it means all winners must have erred (probably made mistake).

Similar to the measurements of errors, *missedopmax* includes all GCAs in which missed opportunities might occurs, however it is more sensitive to outliers. Whereas *missedop* is more conservative but might underestimate missed opportunities especially when number of auctions within GCA is large. The lists of all other variables are contained in Table 4-2.

4.4.2 Testable Hypotheses

The rational way for bidders in competing auctions to bid is to place their bid on the lowest standing bid as showed in theoretical literature by Peters and Severinov (2006). Consequently, once the auctions have ended, the closing price of sold items should always be lower than reservation price of unsold items within the same group of competing auctions (GCAs). We define the instances when this condition was not met as *missed opportunities* and the positive difference between the winning bid of the sold item and the reservation price on unsold tickets in each GCA as *errors* in the previous section. If bidders are rational and market is efficient we then should expect *missed opportunities* to be zero or near zero. Also, *errors* should be zero or not monetarily significantly higher than zero if the cases where *missed opportunities* occur. Therefore, there are two hypotheses we would like to test in this study, as follows:

Hypothesis 1. *Missedopmax* and *missedop* will be equal to zero.

Hypothesis 2. *Errormax* and *errormin* will also be equal to zero.

4.4.3 Research Method

As mentioned in the introduction, the aim of this paper is to determine whether bidders in the group of competing auction (GCA) always bid for the lowest standing bid as prescribed by Peters and Severinov (2006) or deviate from that prescription and creating 'missed opportunity' as described in previous section. In the next session, we will examine the incidence of 'missed opportunity' using various definitions of it. Further, we will observe further the size of it in the case where missed opportunity occurs. Also, we will try to discern the variables affecting missed opportunity and its size.

As described earlier, goods are assumed to be identical in most competing auctions references despite how they are generally substitutable while not identical in real world setting. In general, the tickets auctioned within GCA and across CGA are not homogenous in quality. Japan ticket market unique feature however enables us to explore what happens when products have more homogenous quality (no seating information). We wonder if this feature affects people's bidding behavior, such as lowering mistake occurrences. Thus, we divide the sample categories into 'Overall' group that contains both GCAs with homogenous tickets and GCAs with auctions offering substitutable tickets with differentiated quality and 'Uncertain' group, which contain ticket with presumably the same quality and analyze 'missed opportunity' that occur in each category.

Although the tickets qualities within GCA itself are homogenous, sellers who sell it might possess different credibility. Consequently, although bidders should bid on the auction with the lowest reservation price or standing bid since the ticket is identical, they might not do so. Therefore, next we inspect further the case when seller is identical within GCA.

Later, we will limit the analysis to only AKB48 tickets because although tickets auctions within GCA are for the same concert and artist, they differ across GCA. Further, while the tickets itself offer the same seat quality, there are still some differences exist across auctions, even in the same GCA. Some of the tickets might be auctioned only in pairs and some sellers might employ Buy It Now options. Therefore, we will explore if bidders still deviate and how large is the deviation when these heterogeneities decrease as described in Figure 4-2.

4.4.3.1 Descriptive Statistics

In order to find out the answers the research questions, we employ variables we have defined earlier and use its descriptive statistics.

1. We use mean of *missdopmax* and *missedop* to find out in how many GCA did bidders erred in various settings.
2. We use *errormax*, and *error* to find out how large is the deviation from the lowest standing bid [26] and its distribution.

4.4.3.2 Regression Method (Contingent Factors)

In order to examine the variables affecting missed opportunity, we use regression analysis. Suppose

$$\boldsymbol{m_{is} = \alpha + X_{is}\beta + z_i + \epsilon_{is}} \ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{1})$$

$\boldsymbol{m_{is}}$ is binary variable *missedopmax* or *missedop* for artist *i* and GCA *s*, where *X* consists of the control variables for every GCA. The equation is estimated using linear panel regression with fixed effect to control for heterogeneity bias and probit regression.

Similarly, we use the equation below in order to find out the determinants of error

$$\boldsymbol{y_{is} = \alpha + X_{is}\beta + z_i + \epsilon_{is}} \ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{2})$$

$\boldsymbol{y_{is}}$ is natural log value of *errormax* or *error* for artist *i* and GCA *s*, where *X* consists of the control variables for every GCA. The equation is estimated using linear panel regression with fixed effect to control for heterogeneity bias when errors are larger than

[26] We will also use other measures such as dividing error variables with minimum standing bid (unsuccessful) and dividing error variables with ticket's face value to find out the relative value of the deviation.

zero and panel tobit regression with Mundlak (1978) correction.[27] However due to sample limitation, both equations will only be estimated using linear panel regression with fixed effect for identical sellers case.

4.5 Results

4.5.1 Missed Opportunities

4.5.1.1 Baseline Results

Figure 4-3 depicts the incidence of missed opportunities across three of our data categories. Looking first at the bars in the middle, the mean value of *missedopmax* shows that in more than 40% of 182 GCAs at least one person erred and missed an opportunity in the case where tickets quality is homogenous within GCAs (Uncertain). However, only in about 20% of those GCAs all the successful buyers erred, as indicated by mean of *missedop*.

In Overall dataset, some GCAs contains tickets that are slightly different from each other. In this case, *missedopmax* is more than 50%, which is slightly higher than Uncertain case. It is also true for *missedop* although the difference is not as large. These results are probably due to slight heterogeneity in the goods' quality.

The right side shows average value of missed opportunities for AKB48, which is subset of Uncertain case. The figures for this case are the highest compared to Uncertain and the Overall data. At least a buyer erred in almost 80% of the 43 GCAs and the mean of *missedop* is about 30%. This implies that the figures for other average artist in Uncertain case is probably low.

[27] This is done by assuming that the relationship between $X_{is}$and $\varepsilon_i$can be written as $\varepsilon_i = \bar{X}_i\alpha + v_i$ where v_i is iid ~ follows the normal distribution and is independent of X_{is} and $\boldsymbol{\epsilon_{is}}$ for all i and s. In practice Mundlak corrections can be applied by including the artist average (across GCA) for each of the GCA varying explanatory variables in the right-hand side of Equation 2.

We then divided the GCAs into two categories; one with number of auctions more than 20 and the other less than or equal to 20 as shown in Figure 4-4. We chose 20 since that is the default number of auctions listed per page when you perform a keyword search on Yahoo Japan Auction. Therefore, we suspected that it might affect 'missed opportunity'. From the figure above, we can see that both *missedopmax* and *missedop* are higher among GCAs with more than 20 auctions. Also, *missedopmax* occurred in all those GCAs[28]. The rate for *missedop* is around 40% except for AKB case, which reach 60%.

4.5.1.2 Identical Sellers

While we have showed that people do not always bid on the auction with the lowest reservation price even when the goods' quality is almost identical and generate a 'missed opportunity', in the real online auction setting there might be other reason why they do not follow the strategy. Sellers' credibility, method of payment, and shipping policy usually vary in real online auction setting. It might be the case that some buyers bid on the auction with higher feedback score although it also has higher reservation price. In this section, we examine if 'missed opportunity' still occurs when seller is identical within GCAs.

The sample estimates presented in Figure 4-5 are quite similar with the one in the basic results. However, we can observe that *missedopmax* are lower for all categories while *missedop* are a little higher. This is probably due to similar pricing strategy for reservation price since seller is identical within GCAs.

[28] There are 8 GCAs with more than 20 auctions, all of them are with auctions tickets with homogenous quality (Uncertain) and 5 of them are AKB48 GCAs.

4.5.2 Size and Distributions Errors

Conditional on 'missed opportunity' generated within GCA, we now examine, how large it is and its distribution. We observe that in general, it dies down. Large mistake occurs less frequently than small ones, although there are some exceptions and clustering when number of auctions in GCA is more than 20.

4.5.2.1 Basic Results

4.5.2.1.1 Homogenous Tickets Quality (Uncertain)

Figure 4-6 shows the size of 'missed opportunity' when ticket quality is homogenous within GCAs. The left ones depicted the distribution of *errormax*. When N<20, half of the errors are above ￥5000. While fewer errors occurred as the size gets larger and there are still considerable errors higher than ￥20000 and some buyers even paid more than ￥60000 more than the minimum unsuccessful reservation price. When N>20, *errormax* are more scattered and centered at ￥5000, ￥20000, ￥40000.

The figures on the right are the distributions of *errormin*. The range of the errors is from zero to about ￥50000 which is slightly narrower than *errormax*. Similar to *errormax*, it also dies down although there are some that occur higher than ￥20000. When N>20, when errors occur they are all around ￥10000-￥20000.

4.5.2.1.2 Overall Sample

When we include GCAs with auctions with slightly heterogeneous tickets as shown in Figure 4-7, the figures still look very similar with the Uncertain ones.

However, with the Overall sample and when N<20, the fraction of the errors between zero to ￥10000 are higher, which means among GCAs where tickets are heterogeneous, errors are smaller on average. The distribution of both *errormax* and *errormin* when N>20 are the same since all the GCAs with more than 20 auctions are the ones for Uncertain tickets.

4.5.2.1.3 AKB48

As depicted in Figure 4-8, the distribution of errors for AKB48 GCAs are quite different from other cases. Although AKB48 GCAs are subset of Uncertain GCAs and both are for homogeneous tickets quality, higher fractions of errors are occurring at higher level of yen for *errormax*. They also do not die down as rapidly. However, the sample size for this group is considerably lower.

4.5.2.2 Identical Sellers

In general, redefining GCA to include only auctions from identical sellers causes the rane of *errormax* to decrease. Although they are reduced, the size is still considerable. In addition to that, the average value for *errormin* seems to increase.

4.5.2.2.1 Homogenous Tickets Quality (Uncertain)

From Figure 4-9 we can see higher proportion of small errors (less than or equal to ￥5000) for *errormax* being committed compared to when sellers are heterogeneous within GCA. However errors above ￥10000 are still generated in more than 30% of the GCAs.

Unlike in the previous sections, the proportion of small errors is actually decreasing for *errormin*. On the other hand, the proportion of larger errors is increasing, making the average bigger than in the previous case where sellers are heterogeneous.

4.5.2.2.2 Overall Sample

Figure 4-10 suggests that including GCAs with heterogeneous seat quality does not change the results much. In this case the proportion of small errors are even higher and proportion of bigger errors are lower than in the homogenous quality case.

4.5.2.2.3 AKB48

There are some differences resulted from redefining of GCA in this case as depicted in Figure 4-11. Although there is still quite considerable proportion of large *errormax* generated in this case, the proportion is not as large as before. However for *errormin* the decrease in proportion is not as large, similar to the Uncertain case. There is also a jump in proportion at ￥20000-￥25000 level. These results suggest that seller heterogeneity might affect *errormax* distribution more in this case.

4.5.3 Relative Monetary Size of Errors

4.5.3.1 Errors Relative to GCA's Minimum Unsuccessful Reservation Price

Although ticket quality is homogenous, around 35% of *errormax* generated is higher than GCAs' minimum bid when N<20 as shown in Figure 4-12. While most *errormax* generated are below 5 times of GCAs' minimum bid for unsuccessful auctions, some of them are more than ten times of minimum bid although the share is very small. Meanwhile, when N>20, *errormax* are zero to ten times of GCAs' minimum

bid for unsuccessful auctions, although the proportion of *errormax* between 5 times to ten times of minimum bid is bigger than that of N<20.

When N<20, around 70% of *errormin* are zero to one time of GCAs' maximum minimum bid for unsuccessful auctions. Meanwhile, size of *errormin* when N>20 is around twice to three times of minimum bid.

4.5.3.2 Errors Relative to Tickets' Face Value

The distributions of errors to tickets' face value are depicted in Figure 4-13. When N<20, *errormax* is higher than face value of tickets in more than 40% of the GCAs. This means at least one buyer err in those GCAs and paid more than the tickets' face value although quality of tickets is homogenous and at least one cheaper option is available in the market. More than 30% of *errormax* are more than twice of tickets' face value, and some of buyers even paid more than ten times of tickets' face value. *Errormax* varies around zero to six times of tickets' face value when N>20 and 70% of them are higher than the face value.

When we use stricter definition of missed opportunity we can see from the lower panel that *errormin* are higher than tickets' face value in ore than 20% of the GCAs. However the highest error is around 8 times of face value and error dies down pretty quickly. All *errormin* for GCAs with more than 20 auctions are around two to three times of face value. Considering all *errormin* for N>20 are around two to three times of maximum minimum bid as well. It is implied that maximum minimum bid of unsuccessful auctions are similar with its face value in this case.

4.5.4 The Effect of Heterogeneity in Seat Quality

In this section we investigate the effect of seat certainty and heterogeneity in seat quality on 'missed opportunity' and its size more closely. We divided our GCAs into four categories. First, 'Uncertain' category, similar to the previous sections, this category contains GCAs that offer tickets with unknown seat quality. 'Medium' category contains GCAs with seat quality equal to median level/floor of the venue. 'Good' category includes GCAs that offer tickets with seat level/floor lower than the median floor of each venue (closer to the stage). Thus, 'Bad' category includes GCAs that offer tickets with seat level/floor higher than the median floor of each venue farther from the stage).

Figure 4-14 displays the proportions of missed opportunity in each category. The proportion of GCAs where *missedopmax* (*missedopmin*) occur for Uncertain category is the same as before, about 45% (20%). Missed opportunities occur most frequently in GCAs where the seat qualities are Good or Medium. The occurrence of missed opportunity when seat quality is bad, is lower than that of Uncertain category.

The distribution of errors for Uncertain category is also the same as before as shown in Figure 4-15. About 55% of the *errormax* are above ￥4000 and it spreads out and some *errormax* even reach ￥40000-￥80000. Although only about 40% of the errors in Medium group are above ￥5000, the proportions of *errormax* around ￥4000-￥12000 are a bit higher than that of Uncertain group. However it dies out quickly afterwards. Meanwhile, about 70% of *errormax* in Good category are above ￥4000, and around 60% of those errors are between ￥4000-￥16000. All of *errormax* generated in Bad category are below ￥8000, however about 20% of them are between

￥4000-￥8000 which is higher in proportion than that of Uncertain and Medium categories.

The distributions of *errormin* for all four categories look really similar to their *errormax* counterpart as displayed in Figure 4-16. Nevertheless the range of the size is decreases by 50%. Also, only less than 10% of *errormin* in Bad category is higher than ￥3000.

4.5.5 Regression Analysis

Previous results show that missed opportunities occur in quite numerous GCAs. It still occurs even when auction within GCAs become more homogenous e.g. ticket quality is identical (unknown), and seller is identical. They also have considerable monetary size when it occurs. However, for Overall sample, there might be some slight differences across GCAs e.g. variation in sellers' feedback might be different across GCA as well as seat quality, and number of auctions per GCA. In this section we observe how these variables are affecting *missed opportunities* and *errors*.

Table 4-3 depicts the results of the regressions. The determinants of missed opportunities are estimated using linear probability model (linear regression with fixed effects) and probit model, which includes artist average variables.[29] The results for *missed opportunities* are presented on column 1-4. Probability of a bidder erred in GCAs in which concert tickets with Good quality are auctioned off, is on average around 40% higher than that of in GCAs where tickets with Uncertain quality are

[29] We also run regressions using conditional fixed effect logit, however since marginal effects depend on the value of the FE that are not estimated and in this case can only be obtained by assuming that fixed effect is zero we do not display it here. The complete results can be found in Appendix, however these three different methods generate similar results.

auctioned off, across observed values of other control variables. The probability for Medium and Bad GCAs are also higher than Uncertain GCAs by 25%-40%. These results suggest that the probability of at least a buyer to err is higher by 25% -40% for Certain GCAs. Also, there is a higher probability that *missed* opportunity occurs in Good GCAs compared to Medium and Bad GCAs. This might occur because the competition to acquire a ticket is fiercer in GCAs with good tickets. Studies by Krueger and Pray (2008) and Leslie and Sorensen (2012) show that the main reason why fans engage in trade in the secondary market is to acquire tickets for the best seats. This might induce competition among bidders to be fiercer in some particulars auctions they are engaging in, which distract them from bidding on other auctions with lower standing bid. This is slightly different from the features of the data captured in bar graphs in previous sections where proportion of *missed opportunities* occurring in Uncertain GCAs is higher than that of Bad GCAs although it is lower than that of Good GCAs and Medium GCAs. We suspect that the regressions results are different since we are not controlling for artist heterogeneity previously.[30]

Other thing that increases the probability of a *missedopmax* to occur in a GCA is an increase in the number of auctions per GCA, one more auction per GCA increases probability of *missedopmax* by 3.8 %. This is probably due to higher cognitive cost or computational effort as there are more auctions to be considered (Bapna et al. (2010), Kayhan et al. (2010)). It might also due to higher chance of an auction to be unseen since it is moved to the next page of listed auctions when buyers perform keyword search.

[30] Results from previous sections show that the missed opportunity rate and its size are large for AKB48 and it makes a little below 20% of Uncertain data. After we control for artist heterogeneity, the missed opportunity rate and its size seem to be smaller for Uncertain case.

An increase in proportion of auctions with Buy It Now option (BIN) decreases probability of an error committed by at least one person in GCA by about 18%. The presence of BIN usually decreases the probability of successful auction, increases reservation price, and decreases winning bid. That might be why it decreases the probability of missed opportunity occurrence. Also, BIN price can serve as reference price for other auctions in the GCA as revealed by Podwol and Schneider (2014). Therefore, bidders in GCAs where auctions with BIN option are present are probably less likely to generate *missed opportunities*. Number of bids per GCA has no significant effect on *missedopmax*. It is also the case for average seller feedback score and its standard deviation. This suggests that seller heterogeneity has no statistically significant effect on *missed opportunity* and that bidders are not bidding on auctions with the lowest standing bid because the difference in sellers' feedback (credibility) among auctions. Regression results show that seller heterogeneity only increases missed opportunity as days to concert getting nearer.

There are some differences in the estimates of Good and Bad between the linear panel regression with fixed effects results and Probit results for *missedop*. However, there is 30% higher chance of all buyers in GCA to err when seat is certain and its quality is Medium compared to the Uncertain case. The effect of other variables on *missedop* is similar to the effect of those variables on *missedopmax*. However, unlike for *missedopmax* an increase in one unit of auction per GCA decreases *missedop* by about 5%. We are not very sure why it occurs. However, in order for *missedop* to be generated, all winners within GCA must err. That is, all winning bids must be higher than the highest standing bid of unsuccessful auctions. One of the possible explanations is that there is a higher probability in GCAs with more number of auctions to contain

auctions with very high reservation set by the sellers since GCAs with higher number of auctions usually comprise of ticket auctions for popular concerts. We will show in later section[31] that dropping these auctions along with other extreme values from our sample that left us with only GCAs with quite large number of auctions leads to an increase in *missedop.* This provides us with justification for this possible explanation. We also find that higher total bids per GCA results in higher probability of *missedop*. Only successfully auctioned items receive bid/s from bidders and each bid increases the standing bid for those successfully auctioned items. Therefore higher number of bids suggests higher probability that the standing bid of sold items is higher than the reservation price of unsold items, creating *missedop*.

Column 5-8 depicts the determinants of *errors* in natural logarithm form. The first two columns are estimated using Linear Panel Regression with Fixed Effects conditional on *errormax* (*errormin*) is bigger than zero while the other two are estimated using Tobit with Mundlak approach by including artist averages of control variables in the regressions. When *errormax*>0, GCAs consist of auctions for Good seat quality concert tickets on average has about 2 times higher error than GCAs containing auctions for Uncertain tickets across observed values of other control variables. The same is true for Bad GCA. Meanwhile, GCAs in Medium category on average has 160% higher *errormax* compared with GCAs in Uncertain category. Also, an increase in the proportion of sellers using BIN option decreases *errormax* by 34% this is probably because winning bid tends to decrease in the presence of BIN option.

[31] In section 4.5.6.1 we section we use the second highest (second lowest) successful bid and the second lowest (second highest) unsuccessful standing bid to calculate missed opportunities and errors.

Meanwhile, although GCAs in Good category has around 2.5 times higher *errormin* than Uncertain GCAs, there is no difference ibetween GCAs in Bad category and Medium category with GCAs Uncertain category. One unit increase in number of auction decreases *errormin* by about 20%. Similar to the case of *missedop,* this is probably due to very high reservation set by the sellers in GCAs with high number of auctions (containing auctions for popular concerts). On the other hand, one unit increase in bid increases *errormin* by 0.5%. Also similar to the case of *missedop*, higher number of bids suggests higher probability that the lowest standing bid of sold items is higher as well, widening its gap with the highest reservation price of unsold items, which in turn increases *errormin.*

When we include observations with zero errors, there are slight changes in the results. The effect of being in Good, Bad, Medium GCAs on *errormax* are the same, only the size become even larger. An increase in number of auctions per GCA increases *errormax* which might be resulted from fiercer completion fiercer competition to win the auction for large GCAs. Meanwhile, as before, an increase in proportion of auctions with BIN option decreases it.

Contrary to the case where *errormin*>0, now average *errormin* for Medium group is higher by 315% compared to that of Uncertain group of auctions.. Meanwhile, there is no difference in average *errormin* for other categories of GCA. However, the effect of number of auctions per GCA, bids per GCA, and proportion of BIN auction do not change although they are larger than before.

Changing *ln(errors)* variables to *errors* divided by tickets' face value does not change these results much, as depicted in Table 4-4. However the effects of Total Bids

per GCA on *errormax/facevalue* becomes positive and significant. This is probably due to the decrease in heterogeneity caused by concerts diversity.

4.5.6 Eliminating Extreme Values

4.5.6.1 Second Prices

Previously, we use the highest (lowest) successful bid and the lowest (highest) unsuccessful standing bid to measure *errormax* (*errormin*). In this section we instead use the second highest (second lowest) successful bid and the second lowest (second highest) unsuccessful standing bid to measure *errormax* (*errormin*) to see what happen when we don't use such an extreme values. The summary statistics for the results can be found on Table 4-5. Generally, the number of GCAs falls since GCAs with small numbers of auctions are dropped from the sample. GCAs fall from 602 to 149. *Missedopmax* and *errormax* increases a little across sample. However, the biggest contrast is that *missedopmin* and *errormin* increases across sample. This probably because we are eliminating some unsuccessful auctions with really high starting price.

4.5.6.2 Eliminating Small Errors

For some bidders, paying a few hundreds yen more for his/her ticket might be preferable than looking for other auction with the lowest standing bid. They probably want to save their time or do not want to expend more searching cost. Therefore, in this section, we explore the change in *missed opportunities* and *errors* if we assume that these small errors are equal to zero. For that reason, we redefine missed opportunities and errors assuming bidders treating errors smaller than or equal to 100 yen as equal to zero errors. Thus, we assume that there is no missed opportunity if errors committed by

bidders are lower or equal to 100 yen. We also explore the case if we increase this limit to 500 yen and 1,000 yen. The effect on missed opportunities can be found in Figure 4-17 and Table 4-6.

We can see that there is almost no change in both *missedopmax* and *missedop* as we assume 100 yen errors or less are equal to zero. Assuming 500 yen errors or less as equal to zero decreases *missedopmax* from 54% to 48% and *missedop* from 27% to 24% for Overall sample. Also, Assuming 1000 yen errors or less as equal to zero further decreases *missedopmax* from 54% to 42% and *missedop* from 27% to 21% for Overall sample. We can see that generally, *missed opportunities* do not change much which indicates that most of errors committed by bidders are monetarily significant since 1,000 yen is equal to about 14% of the average Face Value of the tickets auctioned in this market. Additionally, The decrease in *missed opportunities* in every case is higher for GCAs containing Certain tickets compared to Uncertain GCAs and AKB48. This suggests that quite numerous small mistakes committed in Certain GCAs. However, it is not true for Uncertain GCAs and AKB48 GCAs where the tickets quality is nearly identical. Eliminating small errors will increase *errormax* and *errormin* in every case. However, similar to *missed opportunity* case, the change is not large and the summary can be found in Table 4-7.

4.6 Discussion: Possible Causes of *Missed Opportunities*

4.6.1 Tunnel Vision

The default setting in Yahoo Japan Auction for bidders is to use automatic bid for auctions. To join or bid in an auction bidders are only required to submit their maximum bid and Yahoo will bid on behalf of them automatically until the good is won

or this limit is met. Therefore, some bidders might just put a maximum bid on an auction and leave the rest to automatic bid and might not follow the auction diligently and might not see that there are other auctions with lower standing bid.

In addition, when we conduct a category search, the default is to present bidders with 20 auctions. Some bidders might not realize that there are more than 20 auctions available but they are not presented on the first page. In addition, in the default setting, auctions are not ordered based on the lowest standing bid. Therefore, bidders might not see the auction with the lowest standing bid. As displayed in Table 4-9, we find that when number of auctions in GCA is high (N>20) there are at least 2 people who erred within GCA.

4.6.2 Information Overload

Some GCAs have large number of auctions. The larger the number of auctions contained in a GCA, the more information is received by bidders. Some bidders, especially new bidders, might be overwhelmed by the amount of information that they have to process and find it difficult to decide which auction they should put their bid at and how high should they set their maximum bid. The regression results show that an increase in number of auction leads to an increase in *missedopmax* and *errormax* when we use Tobit. Furthermore, using second prices that eliminates many GCAs with small number of auctions leads to an increase in not only *missedopmax* and *errormax*, but also *missedop* and *errormin.*

4.6.3 Auction Fever

Another possible explanations why bidders erred and create *missed opportunities* is auction fever. Ku et al.(2005) found that people bid for cow fiberglass in live and internet auctions up until seven times of its face value. They claimed that bidders were affected by competitive arousal and escalation of commitment that are the central elements in auction fever that may result in overbidding.[32] Other elements of auction fever that have been explored are expected joy or regret (Adam et al. (2011)), irrational limited attention (Malmendier and Lee (2011)), non-rational herding and quasi endowment effect (Podwol and Schneider (2014)), and change in reference point for high bidder (Erhart et al. (2015)). Figure 4-18 shows that GCAs with more intense competition, which is reflected by higher average number of bids, generate bigger *errormax*. Also, the regression results show that sum of bids have positive and statistically significant impact on *missedop* and *errormin*. It also has positive and significant impact on errormax divided by its face value. Moreover, in the previous section, we also find that around 40% of the errors are higher than the tickets' face value. This is similar with Jones (2011) that found 41% of the auctions Amazon gift cards on eBay ended up with winning bids that were higher than its face value. He credited the overbidding to auction fever, however Boehnke (2013) pointed up that the overbidding might be due to eBay special rewards program and that more than 50% of the gift cards were acquired through Buy It Now (BIN) option that did not involve bidding. As far as we know, there was no special rewards program in Yahoo Japan Auction for tickets auction during our observation period. Figure 4-19 shows the

[32] Competitive arousal may come in the heightened feelings of rivalry and adrenaline rush that bidders may experience in bidding that does not exist in fixed price trading. Escalation of commitment stems from psychological inability to ignore sunk cost (time cost and searching cost for example). Both hinder rational decision making and may cause bidders to overbid.

proportion of auctions with BIN option in our sample. It is around 33%- to 35% for Overall sample and Uncertain sample and around 10% for AKB48. They are considerably lower than the proportion in Jones (2011). Also, as shown in previous sections, AKB48 sample that has the lowest BIN proportion has the highest proportion of *missed opportunities* and *errors*. In addition, the regression results show that BIN has negative effect on *missed opportunities* and errors for our sample.

4.7 Conclusions

This study shows that bidders do not always bid on the lowest standing bid in competing auctions environment although goods are quite homogenous as predicted in theory. In general, at least one auction winner erred in more than 50% of our CGAs. Moreover, all winners erred in 27% of the GCAs. Nevertheless, *missed opportunities* decreases by around 10%-20%when goods are homogenous (tickets auctioned are of uncertain quality). *Missed opportunities* also fall when we define GCA to only include identical sellers.

Although around 50% of the errors are less than ￥5000, some of the *errors* are very large with 20% of them are higher than ￥10000. Moreover, around 40% of those errors are higher than tickets' face value. Nevertheless, the proportion of errors occurring dies out, as *errors* become larger. Also, similar with *missed opportunity*, range of *errors* becomes narrower when goods are more homogenous and when seller is identical within GCA.

While these points are true in general, in some cases rate of *missed opportunities* and size of *errors* are very high irrespective of degree of homogeneity in the goods and in the sellers e.g. AKB48. In AKB48 case, at least one winner erred in 80% of the

GCAs and when this happens, 80% of the errors are higher than ￥10000. Moreover, even when seller is identical, 30% of the errors are higher than ￥20000. Also, in the presence of slight heterogeneity in tickets seat quality, *missed opportunities* and size of *errors* are larger for higher quality goods.

There are many factors that may induce *missed opportunity*, some were examined in this study, such as number of auctions, total bids, and availability of BIN option as shown in the regressions results. While we are not particularly sure why bidders generated missed opportunities, we explored three alternatives why it might occur. First, bidders might create missed opportunity due to tunnel vision induced by auction web design and automatic bidding. Second, it might be due to information overload. The third possible reason is auction fever that can be caused by competitive arousal, escalation of commitment, and other triggers that affect bidders' emotion and in turn their bidding strategy.

CHAPTER 5 CONCLUSIONS

5.1 Introduction

The way concerts tickets for JPOP artists are typically distributed in the primary market causes concerts tickets to be sold without seating quality information for some periods of time in the secondary markets. We generated a unique dataset of online auctions for concert tickets in Japan and used the data to investigate several important features of the secondary market. First, we investigated how auctions' success and closing price were determined in this particular market. Second, we studied how a proportion of buyers in this market create 'missed opportunities' by not placing a bid on the auction with the lowest standing bid for similar and highly substitutable goods.

The data on online auctions for concert tickets employed in this study were collected between July 16th 2012 and July 27th 2012 from Yahoo Japan Auction. It consists of 8,738 individual ticket auctions for around 370 JPOP concerts.

In Chapter 3 we examined the determinants of auctions' outcomes: success and closing price in this unique environment. In particular, we investigated the impact of certainty in seat quality on auctions` success and closing price. The econometrics estimation results showed that tickets that were auctioned with certain seat quality have higher probability of success; this result was robust to changes in econometric methods, control variables, and samples. The effect of seat certainty on auctions' closing price was less clear, it showed positive and significant impact when we estimated the model using Fixed Effect OLS but we found no impact when we used Truncated Regression. However, we found that for top traded concerts, tickets with certain seat quality tend to generate higher closing price taking all other control

variables constant irrespective of econometrics method being used. In addition, we found a similar result when we control heterogeneity by adding cluster averages in the regression.

We also found that as the day of the concert drew nearer the probability of a concert ticket to be successfully sold in an auction rose. However, just like in the seat certainty case, the evidence that days to concert affected Ln(closing price) was not completely clear. Finally, introducing a pre-announcement variable to the equations showed that tickets with uncertain seat quality that were sold before seat quality announcement had lower closing price compared to uncertain tickets that were auctioned after the announcement, while we found no difference in success rate between them. In addition, tickets auctioned with certain quality after seats quality were announced had higher success rate and ln(price) compared to those with uncertain quality.

Relaxing the typical assumption in auction models that auctions are independent of one another, in Chapter 4, we examined whether bidders generate 'missed opportunities' in their bidding strategy by not bidding on the auction with the lowest standing bid. We did that by checking if the reservation prices of any unsold items were below the winning bids on sold items when the auctions end.

The data showed that bidders did not always bid on the lowest standing bid in competing auctions for similar and highly substitutable goods. In general, at least one auction winner erred in more than 50% of our CGAs. Moreover, all winners erred in 27% of the GCAs. Nevertheless, *missed opportunities* decreased to 45% when goods were homogenous (tickets auctioned were of uncertain quality). *Missed opportunities* fell further to 38% when we re-defined GCA to only include identical sellers.

Although half of the errors were less than ￥5,000, around 20% of them were higher than ￥10,000 which is equivalent to around $100. Around 40% of those errors were higher than the tickets' face value and 25% of them were more than twice the tickets' face value. Nevertheless, there were fewer bidders creating errors, as the monetary value got higher. Errors were also smaller when goods were more homogenous (uncertain tickets) and when sellers were identical within GCA. Also, in the presence of slight heterogeneity in tickets seat quality, *missed opportunities* and size of *errors* were larger for higher quality goods.

However, in some cases, rate of missed opportunities and size of errors were very high even when goods were similar and sellers are identical e.g. AKB48. In AKB48 case, at least one winner erred in 80% of the GCAs and when this occurred, 80% of the errors were higher than ￥10,000. Moreover, when seller was identical, 30% of the errors were still higher than ￥20,000.

While we are not particularly sure why bidders generated missed opportunities, we explored three alternatives why it might occur. First, bidders might create missed opportunity due to tunnel vision induced by auction web design and automatic bidding. Second, it might be due to information overload. The third possible reason is auction fever that can be caused by competitive arousal, escalation of commitment, and other triggers that affect bidders' emotion and in turn their bidding strategy.

To the best of our knowledge, this is the first study that explored the unique feature of Japanese concert ticket market. This is also the first study that investigated the effect of quality certainty on auction outcomes. Furthermore, we also contributed to the growing literature of competing auctions by exploring different measures of missed opportunities.

5.2 Policy Implications

5.2.1 Regulations on Tickets Resale and Scalping Activities

Ticket resale and scalping practice have been a controversial debate topic both for general public in general and economists in particular. For economists, despite its distasteful impression ticket resale give to general public, it creates benefits for society as it redistributes tickets to people who value it more. However, despite its benefits, public have an unfavorable view on this practice. It is probably because in resale market tickets are often sold at mark up price, which can reach more than four times their face value (Krueger and Pray, 2008; Leslie and Sorensen, 2013; Billboard, 2014). This in turn raised concerns from artist, agents, promoters, primary market ticket sellers, and fans. Not only that this might hurts consumers' welfare, it might also affect primary market ticket sales and artists' image (Kahneman, Knetsch, and Thaler, 1986; Happel and Jennings, 2001; Rolling Stones, 2014).

Many actions had been taken to limit resale and protect the consumers. One of them is by banning tickets resale through anti-scalping law. Various states in USA prohibit tickets resale above its face value (Boyle and Chiou, 2012). Another attempt to curb resale was attempted by Ticketmaster, which is the market leader for live music ticket selling, by issuing electronic tickets for some concerts which makes resale impossible (The Wall Street Journal, 2009; The New York Times, 2012; Billboard, 2014). Despite these measures, based on a report by Ticketmaster (2010) 20% of tickets sold in primary markets are resold again in secondary market in the USA.

The results of this study provide another alternative on ways to limit ticket resale without explicitly forbidding it or making it impossible. We found that tickets auctioned with uncertain seat quality are less desirable for buyers therefore reducing

the number of ticket resale. The results also suggest that revelations of tickets' quality prevents the price from falling. This probably also makes resold concert tickets become even more undesirable.

Table 5-1 and Table 5-2 show the extent of ticket resale in Japan compared to that in USA based on previous studies. Yahoo Japan Auction's secondary ticket market is the biggest auction market in Japan and accounts for about 80% of the ticket auction market in Japan.[33] The statistics in Table 4-2 show that Yahoo Japan ticket sales account for about 6% of the primary market revenue (ACPC) that is approximately the same as to the USA's situation in 2004 based on a study by Leslie and Sorensen (2013) which is much smaller than US's figure nowadays. There are probably other reasons why Japan concert tickets resale market is relatively small but these common practices of selling tickets by lottery and making the seat quality unknown seem to contribute to it.

Moreover, this practice offers several advantages compared to other measures taken to limit ticket resale. While the use of e-ticket makes resale almost impossible, holding information on seat quality does not impend resale explicitly. Therefore, re-allocation is possible and economic benefits from resale market can still be garnered. People who suddenly cannot attend concert because of schedule conflict can still sell their ticket. People who did not win tickets in primary market and willing to pay more can also buy resold tickets. In addition, one of the reasons artists and concert organizers are reluctant to price discriminate which leads to ticket price underpricing and induces resale is that they are unwilling to be seen as being unfair and gouging their fans. This is hard to achieve if tickets for example are auctioned in primary

[33] Based on statistics provided by Aucfan on successful auctions in July 2012

market. Meanwhile, delaying announcement of seat quality does not create that problem.

5.2.2 The Need for Consumer Protection Regulations in Auction

The findings in Chapter 4 shows that consumers bidding in auctions might suffer from auction fever. This leads them to make mistakes and overbid. Therefore, there is a need for a regulation to protect them. However, there is no consumer protection regulation that specifically addresses this issue.

Cancelling successful bid is generally prohibited both on eBay and Yahoo Japan Auction**.** Bidders can only retract a bid within an hour of bid submission for auctions that ends in less than 12 hours on eBay. It is up to sellers whether buyers are allowed to cancel buying a won item except if there is something wrong with the product e.g. change in description, we found out it was smuggled goods. However, there is no consideration given to psychological condition of the bidders when they are participating in an auction.

The Consumer Contracts (Information, Cancellation and Additional Charges) Regulations 2013 launched by The United Kingdom Government allows consumers to cancel a distance or off premises contract (including online auctions) without any reason within 14 days of contract is entered into. However, this only applies if we buy from a professional trader. Also, in practice every seller has his or her own cancellation policy and we are yet to see if this regulation is effective and enforceable.

In the future, instead of targeting seller, it might be better if consumer protection regulations targets auction markets where auctions take place. A regulation that requires online auction markets to design auction pages in a way that makes it easier to browse for similar auctions might help bidders to see that more options are

available for them. For example, instead of the default 20 auctions per page for auction search results based on keywords, 50 auctions per page default page might enable bidders to see more options. Lawmakers can also require those online marketplaces to launch a warning pop up page automatically if bidders bid more than some monetary limit or if they bid continuously in a short period of time.

5.3 Research Limitations and Further Study

5.3.1 Research Limitations

This study has some limitations that can be corrected in the future. First, the data collecting process extends to only twelve days. That made it impossible to observe the full period evolution from when the ticket first sold in secondary market until the concert day. Second, there are more than 300 concerts included in our dataset and they vary from each other in many ways. This hinders us in analyzing some subjects in more detailed fashion e.g. more detailed measurement of seat quality. A more focused future research on fewer auctions and longer time period will provide more insight on this research topics. There are also some information that is not available in this study such as type of sellers, length of auctions, and the detailed bidding process that might provide better understanding on auctions' outcomes and missed opportunities in auctions. Also, a better understanding in psychology, sociology, and anthropology that we do not possess might help us better understand why the practice of delaying quality announcement is practiced in Japanese tickets market and is accepted by concertgoers.

Leaving aside these limitations we think we have provided new insights on how auctions markets work and how, in particular the secondary market for concert tickets operates in the second largest market in the world.

5.3.2 Further Studies

This is a market that is unique and can provide us with rich amount of data. It also enables us to test economics theory empirically in a way that might not be possible to be tested in other natural settings. There are several subjects that deserved to be further explored in the future studies. First, additional data would enable us to explore and test various reasons why bidders generate missed opportunities. The results of that study would enlighten us on how to mitigate this inefficiency and form better policy recommendation.

Dynamic pricing theory is another interesting research topic that can be studied further. The way concert tickets usually sold in Japan is phased through series of lotteries. In addition, there is also announcement on seating in between the time seats are sold and the concert date. This must affect the dynamic pricing of the tickets in secondary market. Therefore, the results of the research could be different from the results of the existing studies conducted on this subject.

Another interesting aspect to be investigated is the welfare effect of the practice. As discussed in Chapter 2 and Chapter 3, concert tickets are rarely price discriminated and underpriced. It is also usually sold through lottery with unknown quality. If the data is available, it will be interesting how it affects artists' revenues and consumer surplus. It will also be interesting to find out if it is the best practice compared to price discrimination as well. In addition, the size of resale market for concert tickets in Japan is small compared to USA, Finding out the welfare effect of resale might be an interesting subject too.

Recently, there are more online concert tickets marketplaces appeared in Japan. In their competition, they offer some different options of guarantee to protect their buyers. However, unlike in USA where this guarantee is typically compulsory, in

Japan they are optional. If the data is available, we might be able to conduct an empirical study on consumers' attitude towards risk.

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Table 2-1: Japan Live Music and GDP Growth

Year	Live Music Annual Sales (billion ￥)	Live Music Sales Growth (%)	Annual Nominal GDP (billion ￥)	GDP Growth (%)	Live Music Industry Sales to GDP (%)
2000	82.59	1.46	510,834.70	0.8	0.02
2001	77.65	−5.98	501,710.70	−1.8	0.02
2002	87.62	12.84	498,008.70	−0.7	0.02
2003	94.28	7.60	501,889.10	0.8	0.02
2004	90.09	−4.44	502,760.80	0.2	0.02
2005	104.93	16.47	505,349.40	0.5	0.02
2006	92.48	−11.87	509,106.40	0.7	0.02
2007	104.06	12.53	513,023.30	0.8	0.02
2008	107.50	3.30	489,520.10	−4.6	0.02
2009	125.50	16.75	473,996.30	−3.2	0.03
2010	128.04	2.02	480,527.50	1.4	0.03
2011	159.62	24.67	474,170.50	−1.3	0.03
2012	170.14	6.59	474,635.70	0.1	0.04
2013	231.83	36.26	483,075.10	1.8	0.05

Source : All Japan Concert and Live Entertainment Promoters Conference (ACPC) and Japanese Government Cabinet Office

Table 2-2: Characteristics of Japan Concert Industry

Japanese Concert Market	Concert Market in Other Countries
Tickets are mostly sold through lottery method	Tickets are mostly sold through first come first served basis
Rarely price discriminated	Generally discriminated into more than 2 price levels
Seating arrangement is usually unknown when buyers buy/win tickets	Seating arrangement is usually known before and when buyers buy/win tickets.

Table2-3: Kanto Area ACPC Statistics 2012

Kanto Area ACPC Statistics 2012	
Performances	7,649
Mobilization (in 10000 people)	1,656.9
Total Sales (in million yen)	81,516
Average Total Sales per Attendant (in yen)	4,919.9

Source: ACPC, Retrieved December 23, 2014 from http://www.acpc.or.jp/marketing/index.php

Table 3-1: Variables' Definition

Variables	Definition
Auction Variables	
success	Dummy variable that takes the value of one if ticket is successfully auctioned off and zero otherwise
closingprice	Per ticket closing price
	Equal to minimum bid when bid is equal to zero
ln(price)	Natural logarithmic value of closing price
	ln(closingprice+1)
Seat Certainty	Dummy variable that takes the value of one if the ticket auctioned contains seating information and zero otherwise
Face Value	The price of the ticket in primary market that is set by promotor/concert organizer
Ln(FV)	Logarithmic term of Face value
	ln(Face Value+1)
Minimum Bid	Starting Bid of the ticket auctioned set by the seller/auctioneer
	(in yen)
Minbid/face value	Minimum bid price/ Face value of the ticket
Ln(minbid)	Logarithmic term of minimum bid
	ln(minimum bid+1)
Exact	Dummy variable indicating relative value of minimum bid to Face Value
	Equal to one if minbid/face value=1 and zero otherwise
Exces	Dummy variable indicating relative value of minimum bid to Face Value
	Equal to one if minbid/face value>1 and zero otherwise
Seat Quality (Floor Level)	Equal to the floor level where seat is located in the venue
	It is assumed to be on median floor level in the venue when seat certainty is equal to zero (seating information is not known yet)
Relative Quality	Equal to the floor where seat is located compared to (divided by) the total number of the floor in the venue
Good	Equal to one if floor where the seat is located is nearer to the stage compared to median floor of the venue.
Medium	Equal to one if floor where the seat is on the median floor of the venue.
Bad	Equal to one if floor where the seat is located is farther from the stage compared to median floor of the venue.
Days to Concert(dtc)	number of days from when the auction ended until concert date
	(in days/10)
Ln(dtc)	Logarithmic term of Days to Concert
	ln(daystoconcert+1)

dd1	Dummy variable that takes the value of one if number of days from when the auction ended until concert date falls in the first quartile of days to concert(dtc), equal to 1 zero otherwise
dd2	Dummy variable that takes the value of one if number of days from when the auction ended until concert date falls in the second quartile of days to concert(dtc), equal to 1 zero otherwise
dd3	Dummy variable that takes the value of one if number of days from when the auction ended until concert date falls in the third quartile of days to concert(dtc), equal to 1 zero otherwise
dd4	Dummy variable that takes the value of one if number of days from when the auction ended until concert date falls in the fourth quartile of days to concert(dtc), equal to 1 zero otherwise (base category)
dtth1	Dummy variable that takes a value of one if tickets were auctioned one to three days before the concerts and zero otherwise
dtth2	Dummy variable that takes a value of one if tickets were auctioned four to six days before the concerts and zero otherwise
dtth3	Dummy variable that takes a value of one if tickets were auctioned seven to nine days before the concerts and zero otherwise
dtth4	Dummy variable that takes a value of one if tickets were auctioned 10 to12 days before the concerts and zero otherwise
dtth5	Dummy variable that takes a value of one if tickets were auctioned 13 to 15 days before the concerts and zero otherwise
dtth6	Dummy variable that takes a value of one if tickets were auctioned 16 days or more before the concerts and zero otherwise (base category)
Monday	Dummy variable indicating if auction is ended on Monday
	Equal to one if it is ended on Monday zero otherwise
Friday	Dummy variable indicating if auction is ended on Friday
	Equal to one if it is ended on Friday zero otherwise
Saturday	Dummy variable indicating if auction is ended on Saturday
	Equal to one if it is ended on Saturday zero otherwise
Sunday	Dummy variable indicating if auction is ended on Sunday
	Equal to one if it is ended on Sunday zero otherwise
pre-announcement	Dummy variable that takes the value of one is ticket is auctioned before the date of seat announcement and zero otherwise
paired	Dummy variable that takes the value of of one if tickets are auctioned off in pairs and zero if it is a single unit ticket auction
BIN	Dummy variable indicating if an auction has a Buy it Now Option or not. Equal to 1 zero otherwise
Peak Time	Dummy variable that takes the value of one if auction occurred between 10pm-12am and zero otherwise

Reserve	Dummy variable indicating if an auction has a secret reservation price or not. Equal to 1 zero otherwise
Feedback	Seller's overall feedback score
Ln(Feedback)	Logarithmic term of seller's feedback
	ln(Feedback+1)
Feedzero	Dummy variable that takes a value of one if feedback score=0, zero otherwise
Feed100	Dummy variable that takes a value of one if feedback score is between 1 to 100, zero otherwise
competition	The number of auctions offering tickets for the same specific concert in the two hours slot of the observation period
ln(compet)	Logarithmic term of competition
	ln(competition+1)
reselln	The number of times ticket has been re-auctioned/relisted during observation period
Venue Variables	
mfloor	The highest (away from stage) floor level in the venue
Tokyo	Dummy variable that takes the value of one if concert was held in Tokyo, zero otherwise
capacity	Capacity of the venue (in 1000)
Ln(capacity)	Logarithmic term of capacity
	ln(capacity+1)
Artist/Concert Variables	
superstar	Dummy variable that takes the value of 1 if the artist has a million record sales certification from RIAJ, zero otherwise
hits	Dummy variable that takes the value of one if the artist has a single or album that charted on Oricon Monthly chart from January 2012- July 2012, zero otherwise
Band concert	Dummy variable that takes the value of one if concert was starred by a solo band, zero otherwise
Festival Band	Dummy variable that takes the value of one if concert was a festival band, zero otherwise
Solo	Dummy variable that takes the value of one if concert was starred by a solo singer, zero otherwise
FM	Dummy variable that takes the value of one if concert was a Fan Meeting, zero otherwise
Musical	Dummy variable that takes the value of one if concert was a musical, zero otherwise
Active year	Number of yeqr the artist has been active until 2012
Ln(active year)	Natural logarithm of active year
Full Lottery	Dummy variables that takes the value of one if tickets were distributed through Full Lottery method in the primary market, zero otherwise
Mixed Lottery	Dummy variables that takes the value of one if tickets were distributed through mixed of lottery method and public released in the primary market, zero otherwise

First Come First Served	Dummy variables that takes the value of one if the tickets were distributed First Come First Served, zero otherwise
mrecord	Dummy variable that takes the value of one if the concert is involving two record companies or more and zero otherwise
multimana	Dummy variable that takes the value of one if the concert is involving two management companies or more and zero otherwise
bigrecord	Dummy variable that takes the value of one if record company`s concert tickets are in the top 10 companies with most auctioned tickets in the period of observation, zero otherwise.
bigmana	Dummy variable that takes the value of one if the management company`s concert tickets are in the top 10 companies with most auctioned tickets in the period of observation, zero otherwise.
bigprom	Dummy variable that takes the value of one if the promoter company`s concert tickets are in the top 10 companies with most auctioned tickets in the period of observation, zero otherwise.
Grouped Variables	
gr(vars)	The concert averages of the variables above incorporated in Mundlak approach

Table 3-2: Descriptive Statistics of Selected Variables

Variable Name	Mean	S.D	Max	Min	Kurtosis	Skewness	N
Success	0.52	0.5	1	0	1.01	-0.09	8738
Closing Price	11,717.32	11,463.22	200,500	0.5	37.88	3.99	8738
Face Value	6,619.66	2,127.99	30,000	168	8.76	0.08	8738
Minimum Bid	7,660.26	7,864.20	198,000	0.5	103.65	6.48	8738
Minimum Bid/Face Value	1.15	1.04	25.38	0	93.48	6.27	8738
Seat Certainty	0.63	0.48	1	0	1.28	-0.53	8738
First Come First Served	0.07	0.25	1	0	13.24	3.5	8738
Full Lottery	0.09	0.29	1	0	9.27	2.88	8738
Days to Concert (in 10 days)	3.39	3.95	22.5	0	7.55	2.18	8734
Seat Quality (Floor Level)	1.84	0.8	5	1	3.02	0.67	8738
Paired Tickets	0.26	0.44	1	0	2.25	1.12	8738
Feedback	1,522.78	3,970.07	39,778	-1	44.47	6.01	8738
Peak Time (10pm-12am)	0.97	0.18	1	0	28.48	-5.24	8738
Reserve	0.002	0.04	1	0	544.13	23.31	8738
Buy it Now (BIN)	0.33	0.47	1	0	1.49	0.7	8738
Venue Capacity (in 10,000)	1.6	1.74	5.8	0.02	3.4	1.27	8738
Artists' Active Year	10.22	7.7	43	0	5.99	1.58	8738
Hits	0.81	0.39	1	0	3.55	-1.6	8738
Superstar	0.27	0.44	1	0	2.07	1.03	8738

Table 3-3: Baseline Results

	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regressions
	success	lnprice	success	lnprice
	[1]	[2]	[3]	[4]
Ln(minbid)	-0.05***	0.05**	-0.10***	0.06***
	[0.01]	[0.02]	[0.02]	[0.02]
exces	-0.16***	0.37***	-0.16***	0.49***
	[0.02]	[0.07]	[0.03]	[0.09]
Seat Certainty	0.14***	0.24***	0.18***	0.03
	[0.02]	[0.07]	[0.04]	[0.11]
Relative Quality	-0.29***	-1.63***	-0.36***	-1.38***
	[0.03]	[0.15]	[0.06]	[0.16]
Ln(compet)	0.01	-0.04	0.01	-0.03
	[0.01]	[0.03]	[0.02]	[0.04]
paired	-0.07***	-0.19**	-0.12***	-0.19**
	[0.02]	[0.08]	[0.03]	[0.08]
Ln(Feedback)	0.01**	-0.02	0.01	-0.04*
	[0.01]	[0.02]	[0.01]	[0.02]
Ln(dtc)	-0.07**	0.14	-0.05	0.02
	[0.03]	[0.10]	[0.04]	[0.08]
BIN	-0.12***	-0.04	-0.17***	-0.08*
	[0.01]	[0.04]	[0.02]	[0.04]
Fstatistics	70	20.59	.	
Chi-square	.	.	1079.78	
N	4826	2278	4530	
Group Number	119	73	103	
Group Max	431	344	.	
Group Min	8	7	.	

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 ,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3-4: Redefining Seat Certainty

	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regressions
	success	lnprice	success	lnprice
	(1)	(2)	(3)	(4)
Good	0.21***	0.39**	0.23***	0.14
	[0.06]	[0.16]	[0.08]	[0.16]
Medium	0.16***	0.16*	0.21***	-0.05
	[0.03]	[0.09]	[0.04]	[0.11]
Bad	0.06	0.21	0.1	0.03
	[0.05]	[0.15]	[0.08]	[0.15]
Relative Quality	-0.08	-1.39***	-0.17	-1.20***
	[0.15]	[0.43]	[0.20]	[0.33]

p*<0.1; ** *p*<0.05; * *p*<0.01 ,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3-5: Top Traded Tickets

	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regressions
	success	lnprice	success	lnprice
	[1]	[2]	[3]	[4]
Ln(minbid)	-0.06***	0.08***	-0.14***	0.08***
	[0.01]	[0.02]	[0.02]	[0.02]
exces	-0.15***	0.19***	-0.19***	0.26***
	[0.02]	[0.06]	[0.04]	[0.09]
Seat Certainty	0.14***	0.37***	0.28***	0.30***
	[0.03]	[0.05]	[0.05]	[0.06]
Relative Quality	-0.30***	-1.81***	-0.44***	-1.68***
	[0.04]	[0.18]	[0.06]	[0.19]
Ln(compet)	0.01	-0.06	-0.06**	-0.10**
	[0.01]	[0.04]	[0.02]	[0.05]
paired	-0.07**	-0.18*	-0.11**	-0.16
	[0.03]	[0.11]	[0.05]	[0.10]
Ln(Feedback)	0.01**	-0.03**	0.01**	-0.03**
	[0.00]	[0.01]	[0.01]	[0.02]
BIN	-0.12***	-0.02	-0.16***	-0.03
	[0.01]	[0.05]	[0.02]	[0.05]
reselln	-0.09***	-0.12***	-0.18***	-0.16***
	[0.01]	[0.03]	[0.01]	[0.03]
Fstatistics	112.23	23.88	.	
Log pseudo-likelihood	-1426.73	-1765.07	-3314.39	
N	3509	1748	3509	
Group Number	47	41	47	

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 ,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3-6: Cluster Averages as Controls

	Baseline		Cluster Averages Added	
	Probit	Truncated Regressions	Probit	Truncated Regressions
	success	lnprice	success	lnprice
	(1)	(2)	(3)	(4)
Seat Certainty	0.17***	0.02	0.23***	0.22***
	[0.04]	[0.10]	[0.04]	[0.06]
Good	0.23***	0.14	0.30***	0.42***
	[0.08]	[0.18]	[0.09]	[0.16]
Medium	0.21***	-0.04	0.26***	0.16**
	[0.04]	[0.12]	[0.04]	[0.08]
Bad	0.1	0.05	0.16**	0.21
	[0.08]	[0.16]	[0.08]	[0.14]

p*<0.1; ** *p*<0.05; * *p*<0.01 ,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3-7: Days To Concert Dummies

	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regressions
	success	lnprice	success	lnprice
	(1)	(2)	(3)	(4)
dtth1	0.12**	-0.24	0.0008	-0.004
	[0.05]	[0.16]	[0.07]	[0.15]
dtth2	0.12**	-0.23**	0.02	-0.09
	[0.05]	[0.11]	[0.06]	[0.13]
dtth3	0.04	-0.02	-0.02	0.07
	[0.05]	[0.09]	[0.06]	[0.12]
dtth4	0.01	-0.10*	-0.03	0.0017
	[0.04]	[0.06]	[0.05]	[0.09]
dtth5	0.01	-0.07	-0.04	-0.04
	[0.04]	[0.05]	[0.04]	[0.07]

*p<0.1; ** p<0.05; *** p<0.01 ,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3-8: Announcement Effect

	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regression	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regression
	success	ln(price)	success	ln(price)	success	ln(price)	success	ln(price)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Seat	0.14***	0.37***	0.28***	0.30***	0.15***	0.24***	0.29***	0.22***
Certainty	[0.03]	[0.05]	[0.05]	[0.06]	[0.03]	[0.05]	[0.05]	[0.07]
pre-					0.01	-0.16**	0.05	-0.09***
announcement					[0.03]	[0.06]	[0.05]	[0.03]
Relative	-0.30***	-1.81***	-0.44***	-1.68***	-0.30***	-1.85***	-0.45***	-1.74***
Quality	[0.04]	[0.18]	[0.06]	[0.19]	[0.04]	[0.18]	[0.06]	[0.19]

*p<0.1; ** p<0.05; *** p<0.01 ,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3-9: Announcement Effect and Seat Quality Dummy

	Linear Panel Regression with Fixed Effects success	Linear Panel Regression with Fixed Effects ln(price)	Probit success	Truncated Regression ln(price)	Linear Panel Regression with Fixed Effects success	Linear Panel Regression with Fixed Effects ln(price)	Probit success	Truncated Regression ln(price)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good	0.20***	0.49***	0.25***	0.24	0.20***	0.41**	0.27***	0.19
	[0.07]	[0.18]	[0.08]	[0.15]	[0.07]	[0.19]	[0.08]	[0.16]
Bad	0.08	0.25	0.25***	0.38**	0.08	0.19	0.27***	0.34**
	[0.05]	[0.18]	[0.08]	[0.15]	[0.05]	[0.17]	[0.08]	[0.16]
Medium	0.17***	0.23**	0.29***	0.19**	0.18***	0.16*	0.31***	0.14
	[0.04]	[0.10]	[0.06]	[0.09]	[0.04]	[0.08]	[0.06]	[0.09]
pre-announcement					0.02	-0.14**	0.05	-0.09***
					[0.03]	[0.07]	[0.05]	[0.03]
Relative Quality	-0.13	-1.50***	-0.44**	-1.94***	-0.13	-1.54***	-0.44**	-1.95***
	[0.16]	[0.53]	[0.18]	[0.38]	[0.16]	[0.53]	[0.18]	[0.38]

Table 4-1: Sample Summaries

	All	Uncertain	AKB48
Number of observations/auctions	2,669	977	423
Number of group of competing auctions	602	182	43
Average number of auctions per group	4.434	5.368	9.837
	(3.785)	(5.582)	(7.306)
Average number of bids per group	35.316	61.538	182.140
	(90.461)	(146.775)	(248.674)

standard deviations are in parentheses

Table 4-2: List of Variables

Variable	Definition
good	Binary variable that equals to one when tickets auctioned within GCA are certain and on the floor lower than median floor of concert venue, zero otherwise.
bad	Binary variable that equals to one when tickets auctioned within GCA are certain and on the floor higher than median floor of concert venue, zero otherwise.
medium	Binary variable that equals to one when tickets auctioned within GCA are certain and on the floor are equal to median floor of concert venue, zero otherwise.
finemarkets	Number of auctions in each GCA
bidmarkets	The sum of number of bids submitted to all auctions in the GCA
liquid	Number of auctions available for each concert for the entire observation period
mbin	Fraction of auctions in each GCA with Buy It Now Option
sdbin	Standard deviation of binary variable indicating availability of Buy It Now option in auctions, calculated for each GCA
mpair	Fraction of auctions in each GCA offering tickets only in pairs
sdpair	Standard deviation of binary variable indicating auctions offering paired tickets, calculated for each GCA
mfeed	Average feedback scores of sellers in GCA
sdfeed	Standard deviation of feedback scores for every GCA
mlevelr	Average quality of saet for each GCA
mbigshop	Fraction of auctions in each GCA offered by seller that has more than 100 listed auctions during observation period
sdbigshop	Standard deviation of binary variable bigshop for every GCA

Table 4-3 Regression Results

	Panel Linear Regression with Fixed Effects (LPM)		Probit		Panel Linear Regression with Fixed Effects errors>0		Panel Tobit with Mundlak	
	[1] missedopmax	[2] missedop	[3] missedopmax	[4] missedop	[5] ln(errormax)	[6] ln(errormin)	[7] ln(errormax)	[8] ln(errormin)
Good	0.467*	0.194	0.424***	0.345*	2.037**	2.495*	6.908***	4.204
	(0.186)	(0.164)	(0.0636)	(0.145)	(0.643)	(1.169)	(1.934)	(2.233)
Bad	0.381*	0.378**	0.250**	0.214	2.001***	0.782	3.490*	2.047
	(0.159)	(0.126)	(0.0852)	(0.123)	(0.539)	(0.937)	(1.664)	(1.679)
Medium	0.437***	0.346***	0.370***	0.304***	1.617*	1.616	4.531***	3.151**
	(0.0960)	(0.1000)	(0.0611)	(0.0868)	(0.616)	(0.990)	(0.955)	(1.020)
Number of Auction per GCA	0.0291***	-0.0420***	0.0389***	-0.0544***	-0.00654	-0.199**	0.248***	-0.466***
	(0.00574)	(0.00979)	(0.0103)	(0.0112)	(0.0268)	(0.0589)	(0.0751)	(0.0883)
Fraction of Auctions with BIN Option	-0.190***	-0.100*	-0.181***	-0.117**	-0.341*	-0.561*	-1.749***	-1.002***
	(0.0502)	(0.0484)	(0.0455)	(0.0407)	(0.156)	(0.263)	(0.358)	(0.295)
Total Bids per GCA	-0.000412	0.00157***	-0.000440	0.00179***	0.00184	0.00527***	-0.00272	0.0136***
	(0.000224)	(0.000283)	(0.000435)	(0.000428)	(0.00115)	(0.00135)	(0.00297)	(0.00269)
Average Feedback Score per GCA	-0.0201	-0.00451	0.00262	0.0192	-0.0481	0.0857	0.0537	0.152
	(0.0206)	(0.0188)	(0.0184)	(0.0166)	(0.0671)	(0.142)	(0.165)	(0.131)
Feedback Heterogeneity (sd)	0.0387	0.0269	-0.0112	-0.0144	0.130	-0.00798	-0.0318	-0.0937
	(0.0302)	(0.0238)	(0.0214)	(0.0171)	(0.122)	(0.148)	(0.233)	(0.187)
Feedback Heterogeneity#Days to Concert	-0.00191**	-0.00161**			-0.00252	0.00725		
	(0.000629)	(0.000547)			(0.00420)	(0.00530)		
Fixed Effects	Yes	Yes	No	No	Yes	Yes	No	No
Artist Averages	No	No	Yes	Yes	No	No	Yes	Yes
N	601	601	601	601	328	164	601	601
N_Clust	101	101	101	101	71	64	101	101

* $p<0.1$; ** $p<0.05$; *** $p<0.01$,panel is at artist level, the coefficients for probit and tobit regressions are marginal effects and average partial effect(APE) respectively

Table4-4: Errors/Face Value as Dependent Variable

	Panel Linear Regression with Fixed Effects errors>0		Panel Tobit with Mundlak	
	[1] errormax/fv	[2] errormin/fv	[3] errormax/fv	[4] errormin/fv
Good	1.019**	2.078**	1.658**	0.655
	[0.495]	[0.895]	[0.657]	[0.411]
Medium	0.536	0.672	0.608	0.29
	[0.428]	[0.727]	[0.519]	[0.295]
Bad	0.438	1.246*	0.911***	0.475**
	[0.361]	[0.676]	[0.328]	[0.187]
Number of Auction per GCA	-0.015	-0.212***	0.034*	-0.096***
	[0.031]	[0.060]	[0.020]	[0.017]
Fraction of Auctions with BIN Option	-0.530**	-0.666**	-0.474***	-0.225***
	[0.208]	[0.296]	[0.104]	[0.056]
Total Bids per GCA	0.004*	0.005***	0.001*	0.003***
	[0.002]	[0.001]	[0.001]	[0.001]
Average Feedback Score per GCA	-0.11	0.051	-0.02	0.029
	[0.113]	[0.142]	[0.046]	[0.025]
Feedback Heterogeneity (sd)	-0.242	0.251	-0.079	-0.009
	[0.244]	[0.335]	[0.066]	[0.036]
Feedback Heterogeneity#Days to Concert	-0.001	-0.007		
	[0.006]	[0.009]		
Fixed Effects	Yes	Yes	No	No
Artist Averages	No	No	Yes	Yes
N	328	164	601	601
N_Clust	71	64	101	101

* $p<0.1$; ** $p<0.05$; *** $p<0.01$,panel is at artist level, the coefficients for probit and tobit regressions are marginal effects and average partial effect(APE) respectively

Table 4-5: Second Prices

	count	mean	sd	min	p25	p50	p75	max
AKB								
missedopmax	18	0.777778	0.427793	0	1	1	1	1
missedop	18	0.333333	0.485071	0	0	0	1	1
errormax	18	16961.28	16125.54	0	3250.5	16111	25000	52000
errormax>0	14	21807.36	15041.07	3250.5	11002.5	19817.5	27200	52000
errormin	18	2713.056	5166.015	0	0	0	1500	15950
errormin>0	14	3488.214	5655.741	0	0	0	8000	15950
finemarkets	18	14.16667	5.447611	4	10	13.5	19	24
bidmarkets	18	200.5556	169.4421	4	82	145	349	625
Uncertain								
missedopmax	41	0.512195	0.506061	0	0	1	1	1
missedop	41	0.219512	0.419058	0	0	0	0	1
errormax	41	1413.415	2601.154	0	0	200	1750	10200
errormax>0	21	2759.524	3103.491	200	800	1750	3000	10200
errormin	41	286.5854	711.251	0	0	0	0	3000
errormin>0	21	559.5238	922.716	0	0	0	700	3000
finemarkets	41	8.268293	2.578996	5	7	8	9	16
bidmarkets	41	41.2439	47.64335	2	9	26	55	244
Certain								
missedopmax	31	0.645161	0.486374	0	0	1	1	1
missedop	31	0.258065	0.444803	0	0	0	1	1
errormax	31	10645.26	14463.23	0	0	3550	19250	52000
errormax>0	20	16500.15	15119.55	250	4025	12251.25	24722	52000
errormin	31	1804.355	4173.195	0	0	0	500	15950
errormin>0	20	2796.75	4957.488	0	0	0	3750	15950
finemarkets	31	13.09677	6.209427	4	9	11	18	28
bidmarkets	31	157.3226	158.3249	4	45	95	219	625
Overall								
missedopmax	72	0.569444	0.498629	0	0	1	1	1
missedop	72	0.25	0.436051	0	0	0	0.5	1
errormax	72	5843.097	11115.14	0	0	500	5750	52000
errormax>0	41	10261.05	13146.43	200	1500	4000	13500	52000
errormin	72	1398.403	4739.997	0	0	0	50	33000
errormin>0	41	2455.732	6100.697	0	0	0	1500	33000
finemarkets	72	10.33333	5.096257	4	7	9	12	28
bidmarkets	72	92.06944	123.4748	2	13.5	48	117	625

Table 4-6: Missed Opportunities Assuming Bidders Ignoring Small Errors

	AKB48	*Uncertain*	*Certain*	*Overall*
missedopmax	0.79	0.45	0.59	0.54
missedopmax100	0.79	0.45	0.58	0.54
missedopmax500	0.77	0.41	0.50	0.48
missedopmax1000	0.74	0.37	0.45	0.42
missedop	0.33	0.22	0.30	0.27
missedop100	0.33	0.22	0.29	0.27
missedop500	0.30	0.20	0.25	0.24
missedop1000	0.26	0.16	0.23	0.21
Total Number of GCAs	43	182	420	602

Table 4-7: Errors Assuming Bidders Ignoring Small Errors

	N	mean	sd	min	p25	p50	p75	max
AKB								
errormax>0	34	23011.51	15904.48	250	12500	22250	33250	70600
errormax100>0	34	23011.51	15904.48	250	12500	22250	33250	70600
errormax500>0	33	23701.26	15626.15	1000	12500	22500	33250	70600
errormax1000>0	32	24410.67	15326.76	2500	13000	22850	34125	70600
errormin>0	14	12525.75	11190.86	500	1250	13025	15200	37410
errormin100>0	14	12525.75	11190.86	500	1250	13025	15200	37410
errormin500>0	13	13450.81	11076.69	1000	2700	15000	15200	37410
errormin1000>0	11	15714.59	10516.17	1250	10750	15000	20000	37410
Uncertain								
errormax>0	82	12458.44	14656.38	50	1800	5725	20250	70600
errormax100>0	81	12611.63	14681.49	125	1800	5750	20250	70600
errormax500>0	75	13592.23	14827.82	550	2500	7250	22500	70600
errormax1000>0	67	15123.39	14973.29	1100	3000	8501	24000	70600
errormin>0	40	7017.76	8818.51	125	1100	3125	10875	37410
errormin100>0	40	7017.76	8818.51	125	1100	3125	10875	37410
errormin500>0	36	7760.71	8998.50	600	1525	3775	11025	37410
errormin1000>0	30	9151.18	9258.55	1200	2700	5625	15000	37410
Certain								
errormax>0	246	5526.04	7500.94	50	1100	3025	7500	70000
errormax100>0	242	5615.93	7529.87	110	1250	3225	7500	70000
errormax500>0	212	6362.77	7761.26	520	2000	4000	8550	70000
errormax1000>0	187	7106.56	7975.81	1100	2500	4899	9000	70000
errormin>0	124	4177.21	5350.48	100	1150	2250	5100	30500
errormin100>0	123	4210.36	5359.56	200	1200	2250	5200	30500
errormin500>0	106	4835.75	5524.23	530	1700	2850	6500	30500
errormin1000>0	95	5306.39	5650.39	1100	2000	3620	7000	30500
Overall								
errormax>0	328	7259.14	10217.79	50	1225	3500	8805	70600
errormax100>0	323	7370.27	10257.27	110	1300	3500	8999	70600
errormax500>0	287	8252.00	10557.12	520	2000	4500	9500	70600
errormax1000>0	254	9221.24	10852.86	1100	2700	5275	10500	70600
errormin>0	164	4870.03	6458.03	100	1150	2375	5875	37410
errormin100>0	163	4899.29	6467.02	125	1200	2450	6050	37410
errormin500>0	142	5577.29	6667.51	530	1700	3025	7000	37410
errormin1000>0	125	6229.14	6853.34	1100	2000	3800	7500	37410

Table 4-8 Missed Opportunities within GCA

Number of Missed Opportunities within GCA	Freq.	Percent
0	274	45.51
1	182	30.23
2	59	9.8
3	41	6.81
4	16	2.66
5	5	0.83
6	7	1.16
7	1	0.17
8	4	0.66
9	3	0.5
10	2	0.33
12	2	0.33
15	2	0.33
18	1	0.17
21	1	0.17
22	1	0.17
30	1	0.17

Table 4-9 Missed Opportunities within GCA when N>20

Number of Missed Opportunities within GCA	Freq.	Percent
3	1	12.5
9	1	12.5
12	1	12.5
15	1	12.5
18	1	12.5
21	1	12.5
22	1	12.5
30	1	12.5

Table 5-1: Japan Concert Ticket 2012 Secondary Market vs Primary Market

Month	Average Transaction Price (in yen)	Number of Successful Transactions	Total Revenue (in million yen)
January	15,503	16,357	253.59
February	14,499	17,917	259.80
March	14,634	23,295	340.90
April	15,629	34,520	539.53
May	18,085	27,015	488.59
June	15,369	22,043	338.79
July	15,673	21,213	332.49
August	17,724	26,325	466.60
September	21,402	26,696	571.36
October	12,826	27,145	348.17
November	15,878	25,556	405.79
December	19,833	38,147	756.55
Yearly Total Yahoo Auction (Secondary Market)		306,229	5,102.16
Yearly Total Kanto ACPC (Primary Market)		16,568,777	81,516.00
Yahoo Size as % of ACPC			6.26%

Table 5-2: Resale Statistics From Previous Studies

	Leslie and Sorensen (2004)	Krueger and Pray (2008)	Bhave and Budish (2010)
Rate of Resale	4%	10%	20%
Average Mark Up	39%	36%	2%*
Size of Resale market compared to Primary Market	6% ($668 mill)	($600 mill)	($4-$10 bill)

* Mark up is estimated against primary market ticket auction price instead of non-auctioned price that is usually employed

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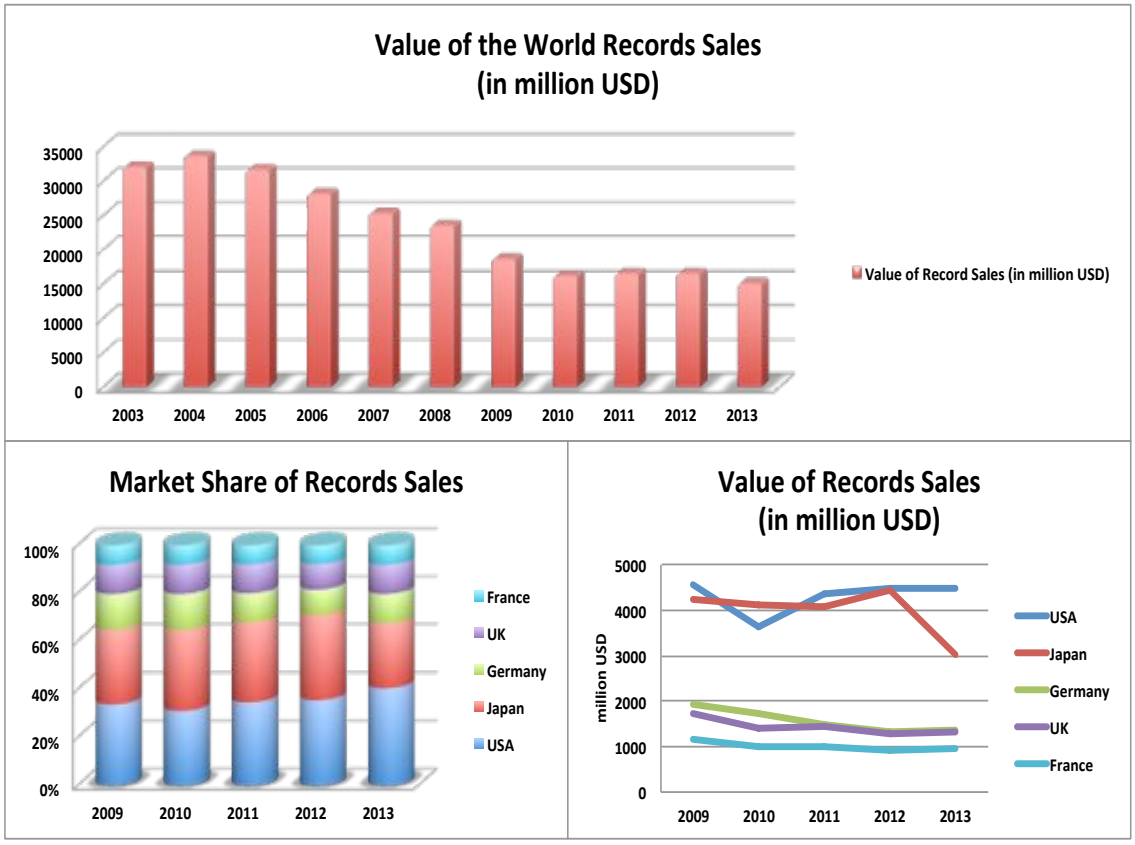
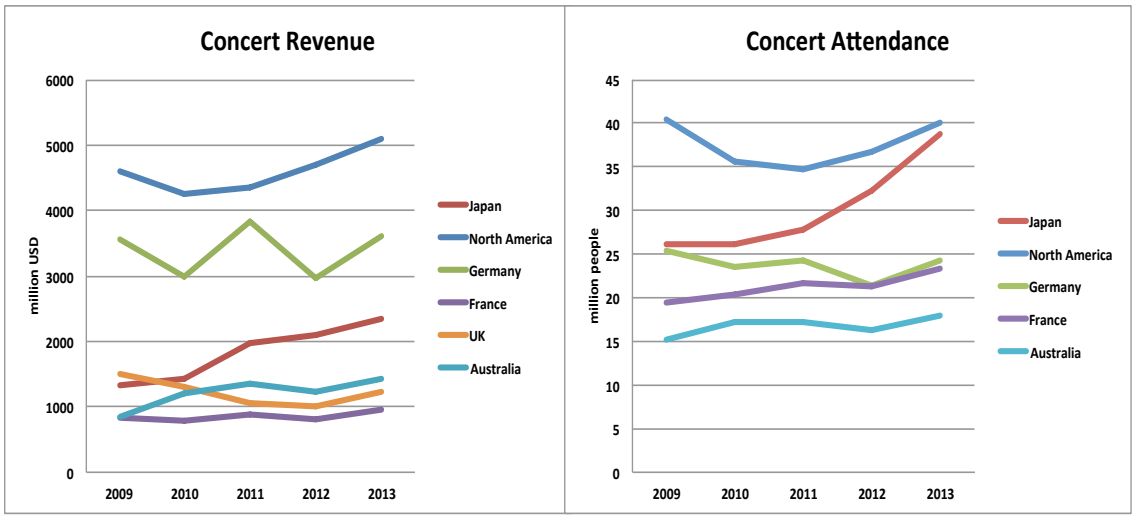
Figure 2-1: World Records Sales



Source: RIAJ Yearly Book 2000-2014

Figure 2-2: Concerts Revenue and Attendance in Major Countries



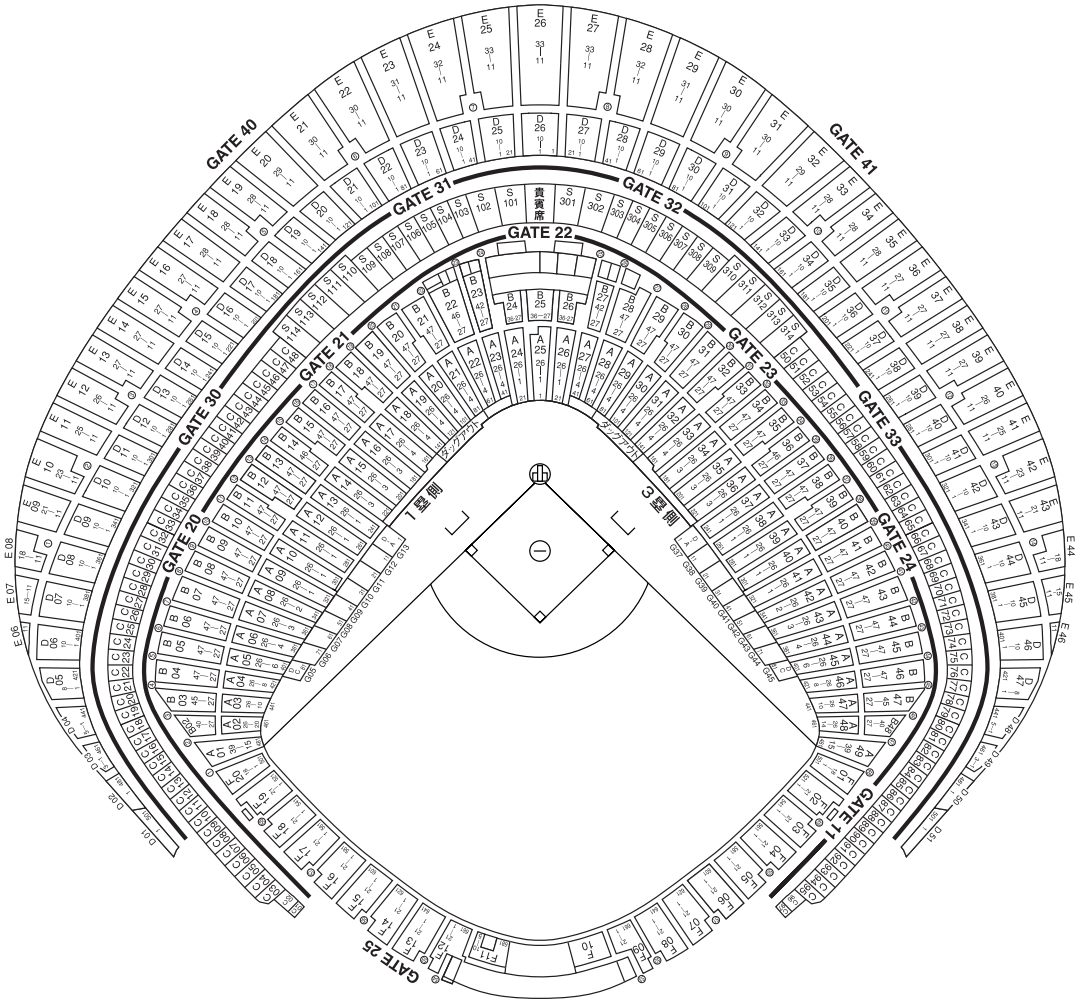
Source: Various sources

Figure 2-3a: AKB48 Concert in Tokyo Dome's Ticket Price

Source: AKB48 website, Retrieved January 20, 2014 from www.akb48.jp/news/detail.php?id=7438

Figure 2-3b: Tokyo Dome's Seating Chart

東京ドーム座席表

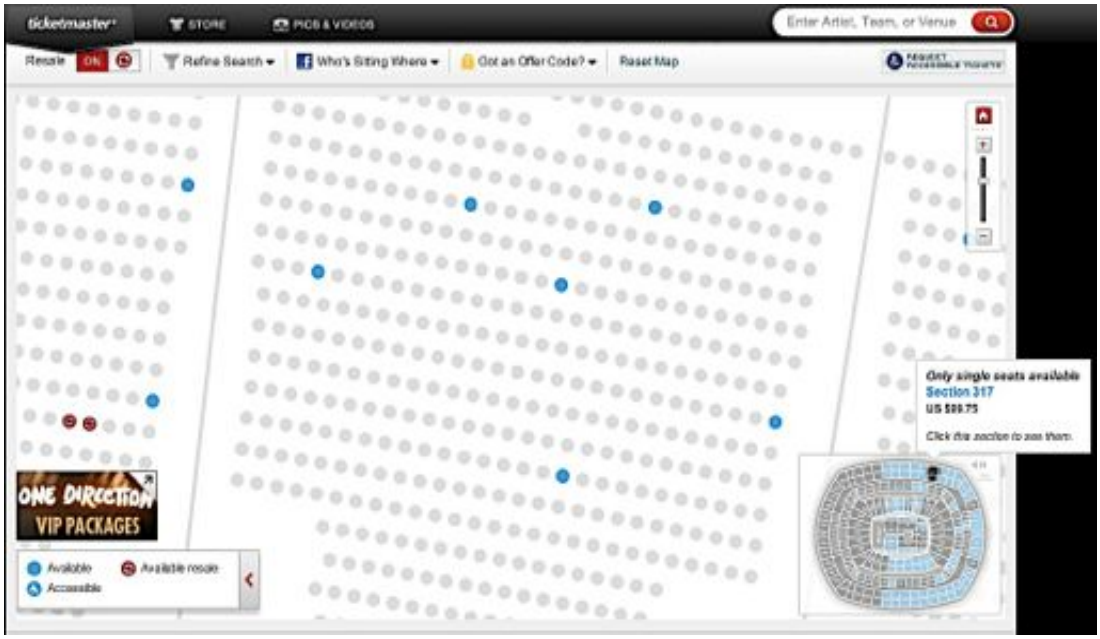


Source: Tokyo Dome website, Retrieved January 20, 2014 from https://www.tokyo-dome.co.jp/dome/events/seat/pdf/seat.pdf

Figure 2-4a: One Direction Concert Ticket Price and Seating Detail at Metlife Stadium

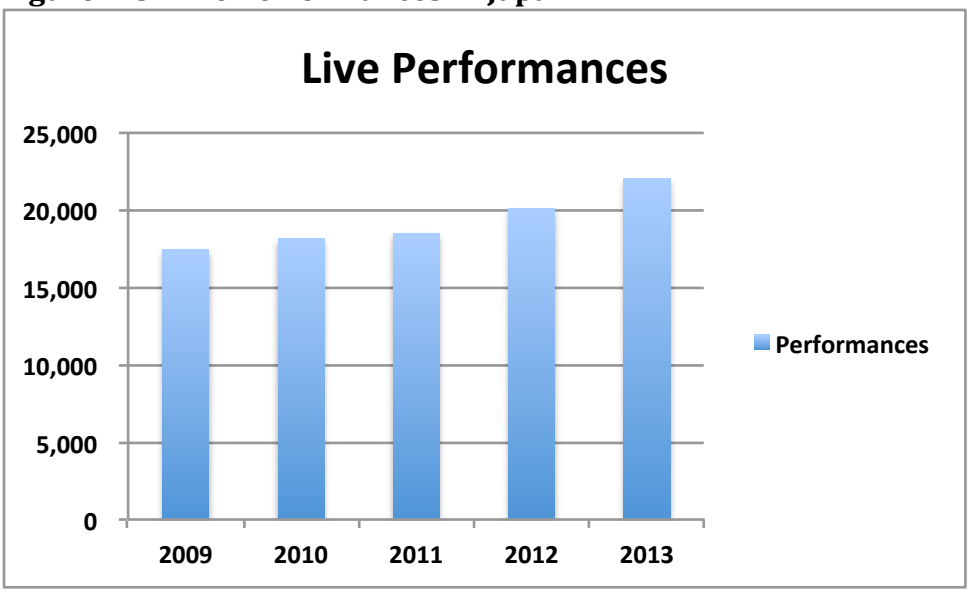
Source: Ticketmaster, Retrieved January 20, 2014 from www.ticketmaster.com/one-direction-where-we-are-tour-east-rutherford-new-jersey-08-04-2014/event

Figure 2-4b: Sections and Seats Available and Its Price for One Direction Concert at Metlife Stadium



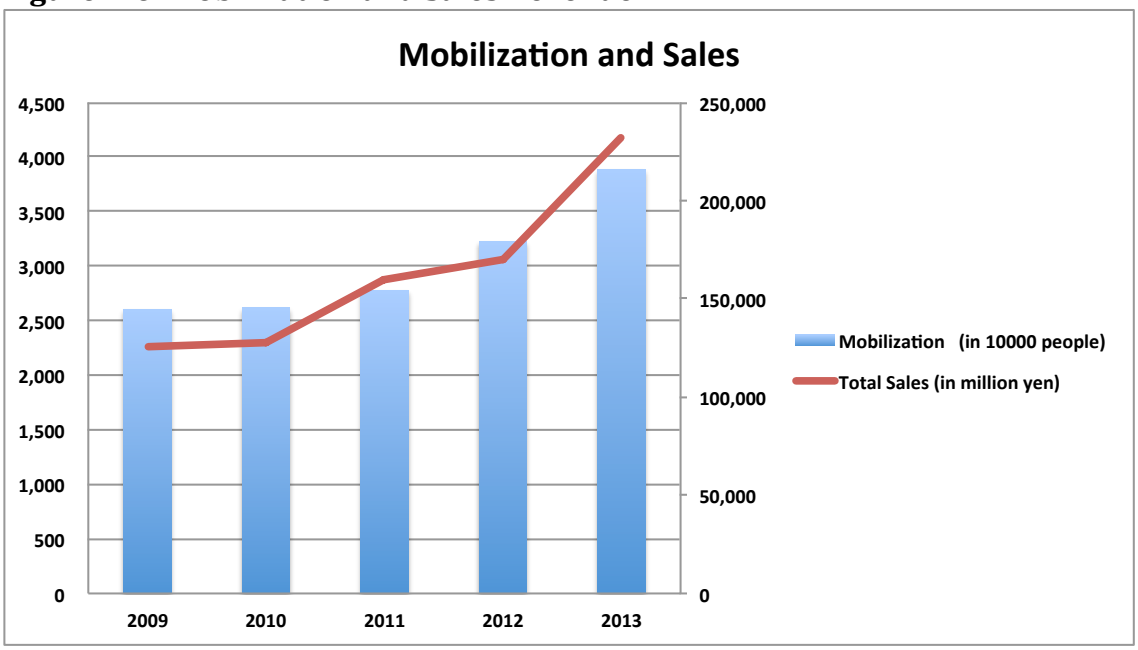
Source: Ticketmaster, Retrieved January 20, 2014 from www.ticketmaster.com/one-direction-where-we-are-tour-east-rutherford-new-jersey-08-04-2014/event

Figure 2-5: Live Performances in Japan



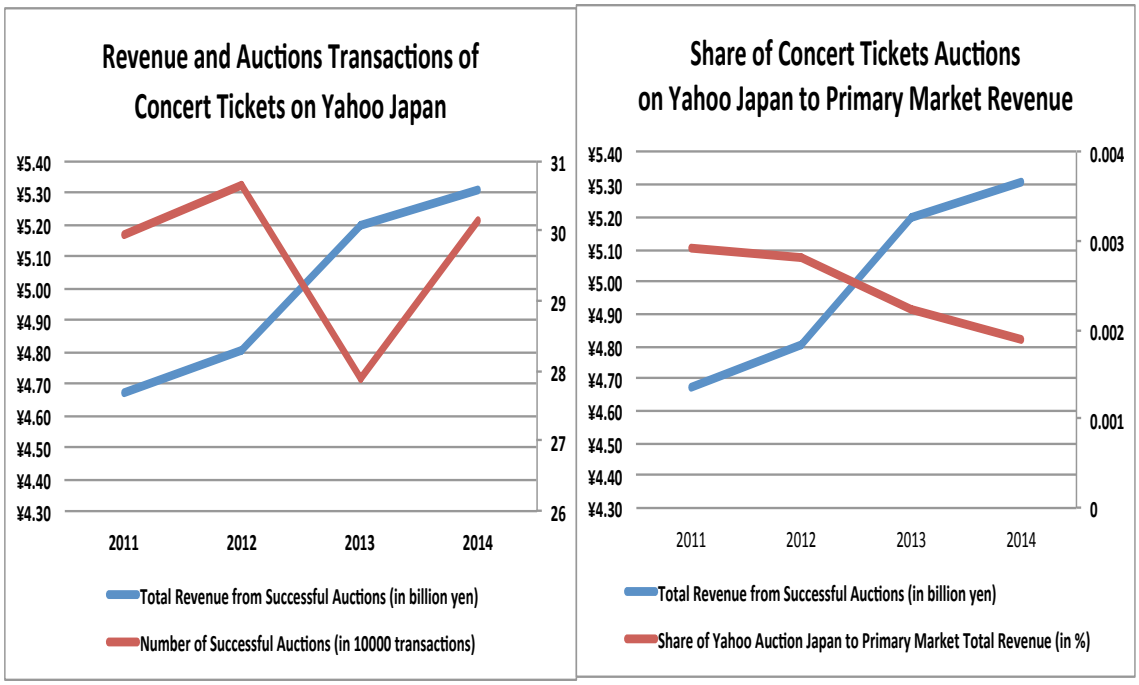
Source: ACPC, Retrieved December 23, 2014 from http://www.acpc.or.jp/marketing/index.php

Figure 2-6: Mobilization and Sales Revenue



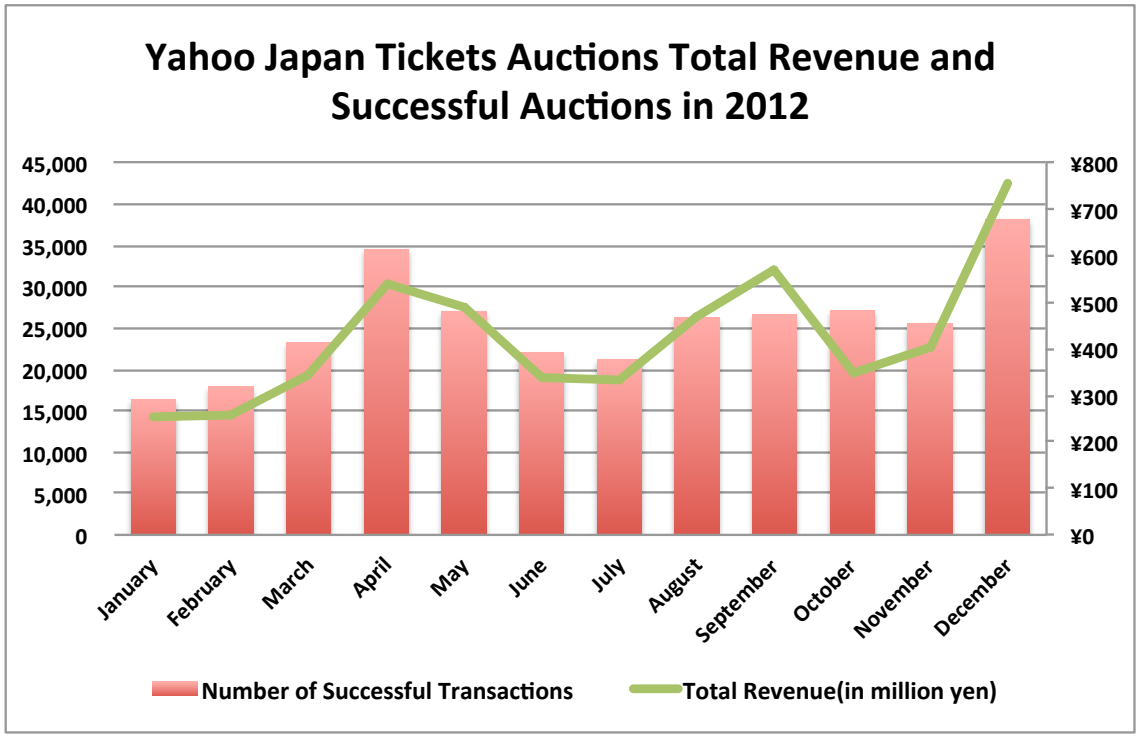
Source: ACPC, Retrieved December 23, 2014 from http://www.acpc.or.jp/marketing/index.php

Figure 2-7: Ticket Auctions on Yahoo Japan Auction



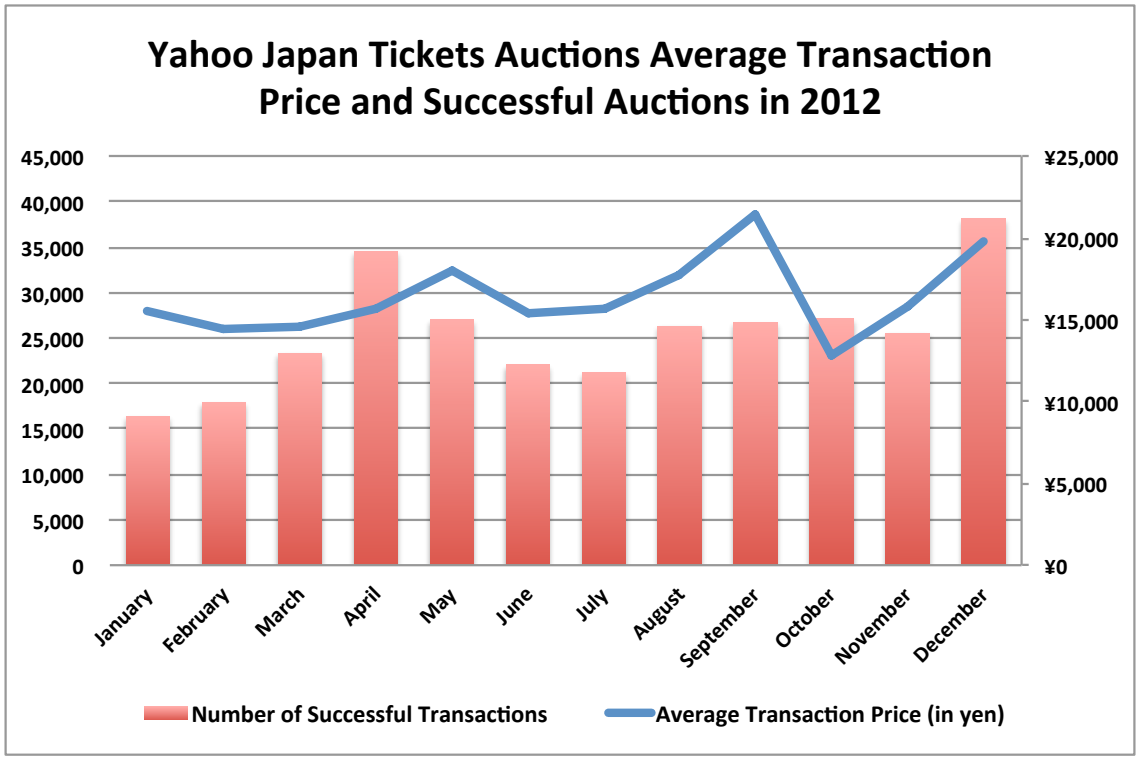
Source: Aucfan , retrieved October 2, 2013, from http://aucfan.com/yahoo

Figure 2-8: Total Revenue and Successful Auctions in 2012



Source: Aucfan , retrieved October 2, 2013, from http://aucfan.com/yahoo

Figure 2-9: Average Closing Price in an Auction and Successful Transaction in 2012



Source: Aucfan , retrieved October 2, 2013, from http://aucfan.com/yahoo

Figure 2-10: Japanese Concert Market Flowchart

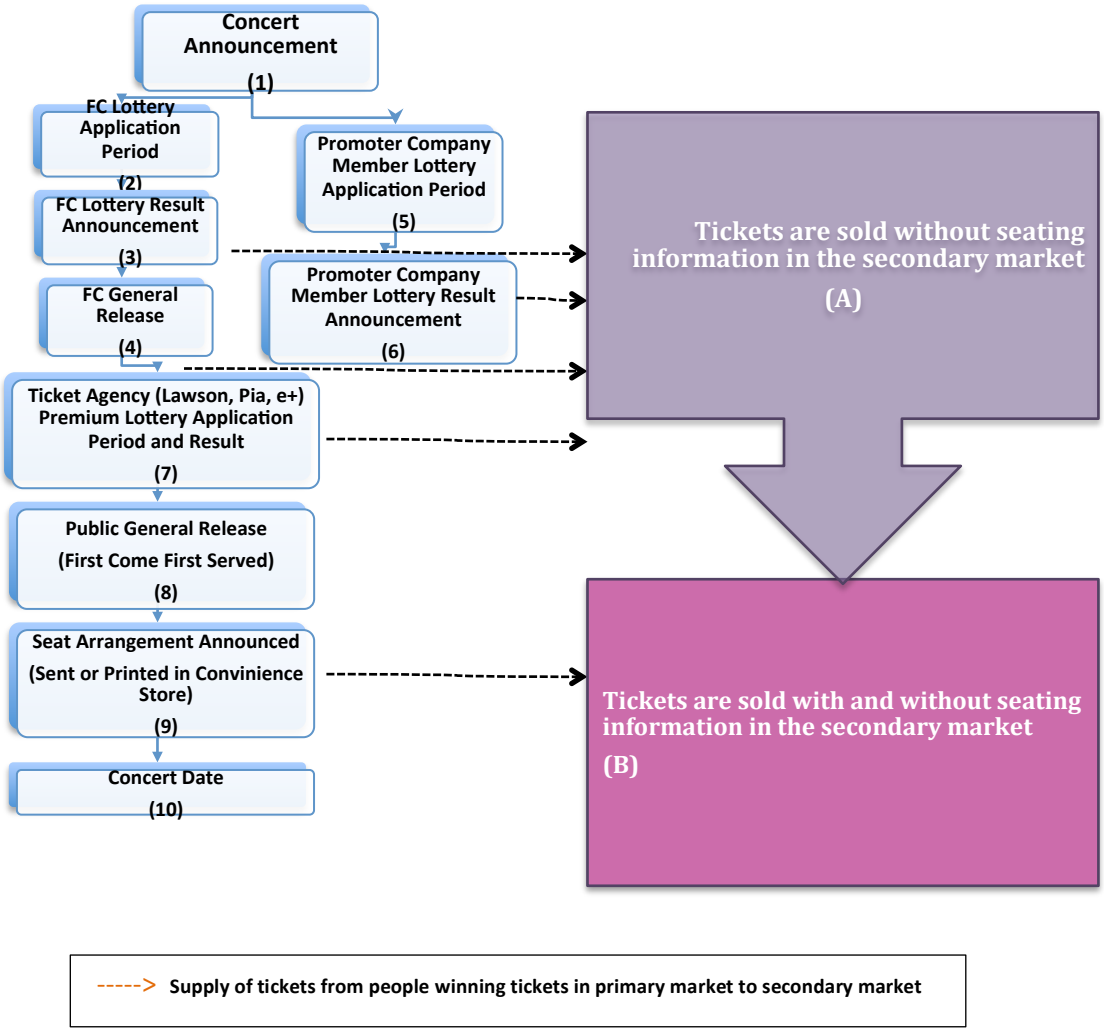


Figure 3-1: Distribution of Seat Quality

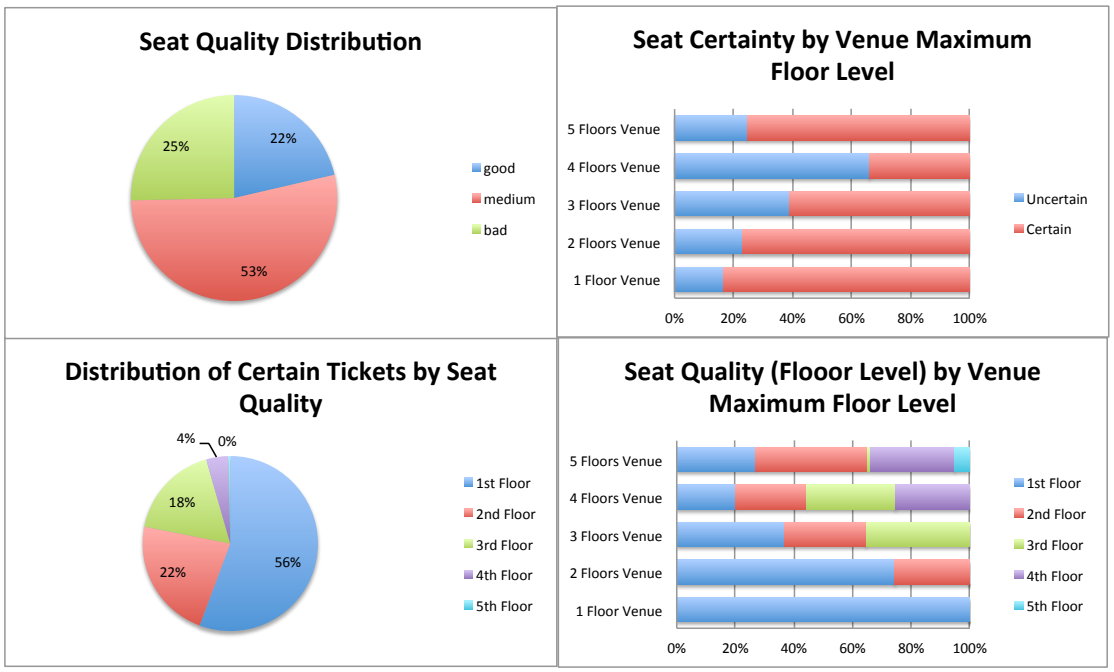


Figure 3-2: Seat Certainty

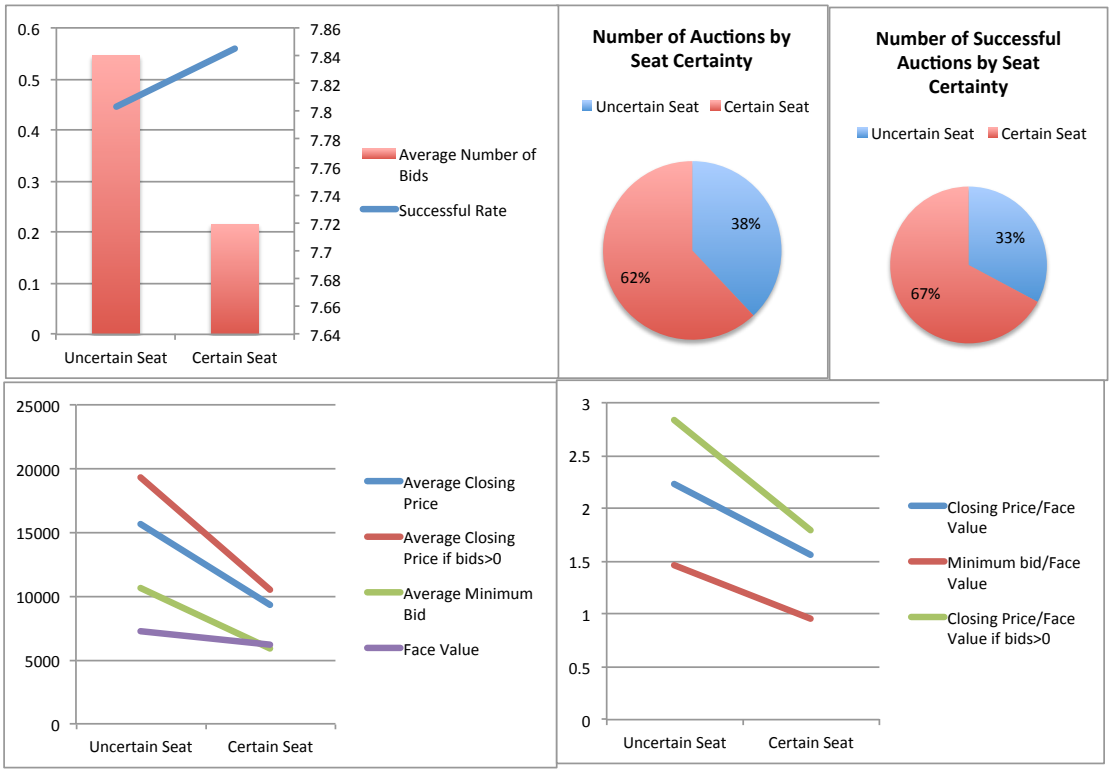


Figure 3-3: Seat Certainty (Status Change)

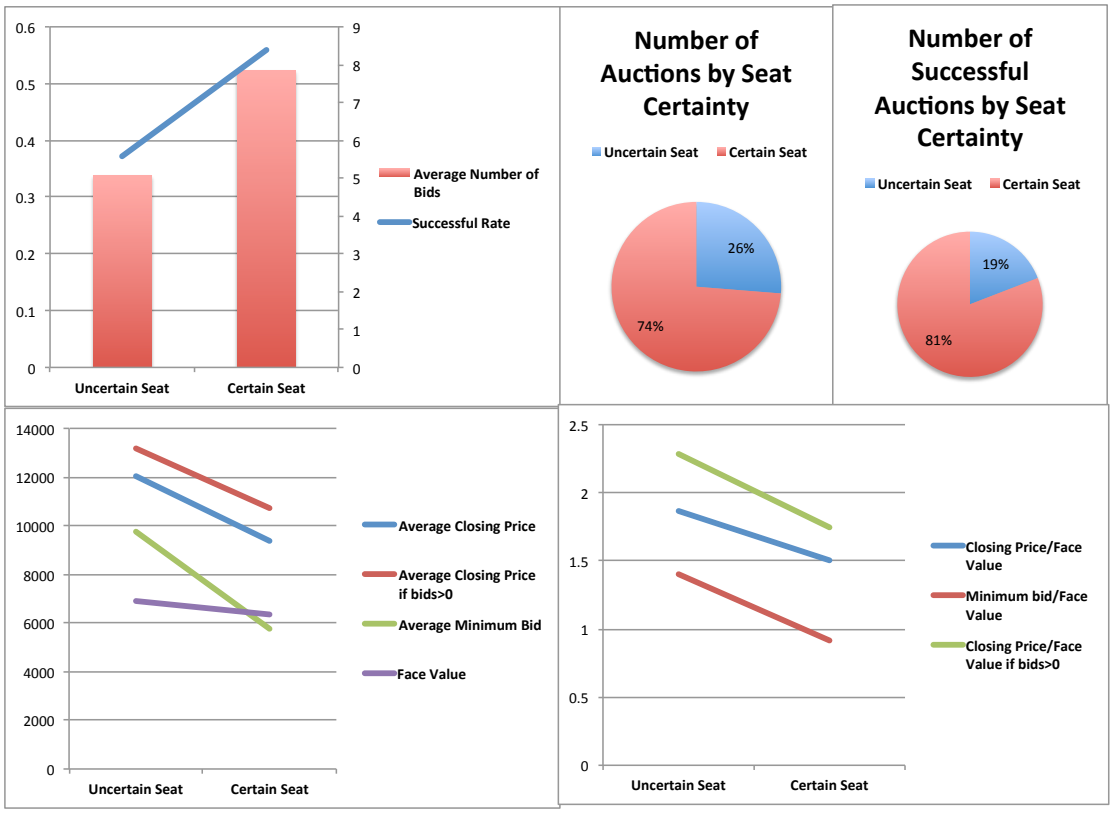


Figure 3-4: Concert Average Seat Certainty and Auction Success

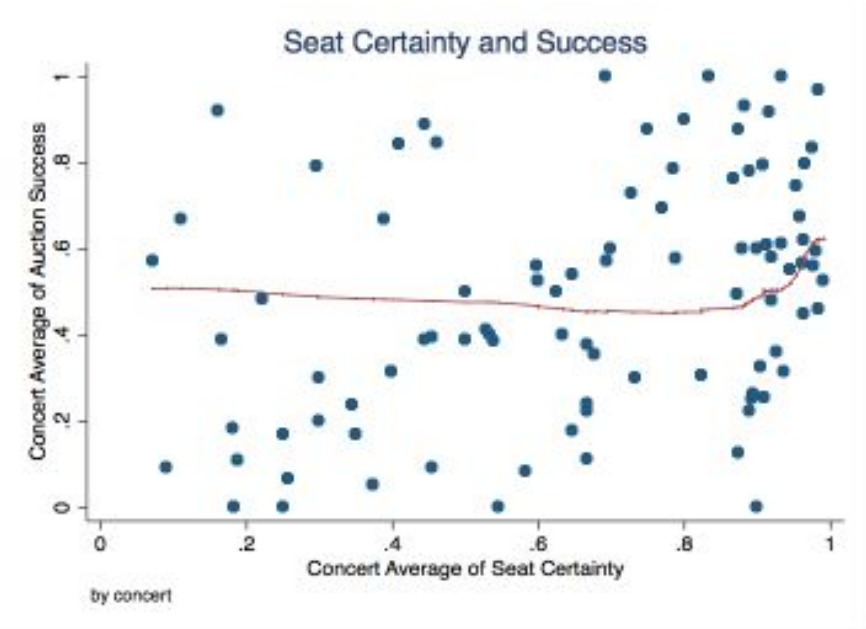


Figure 3-5 Concert Average Seat Certainty and Closing Price

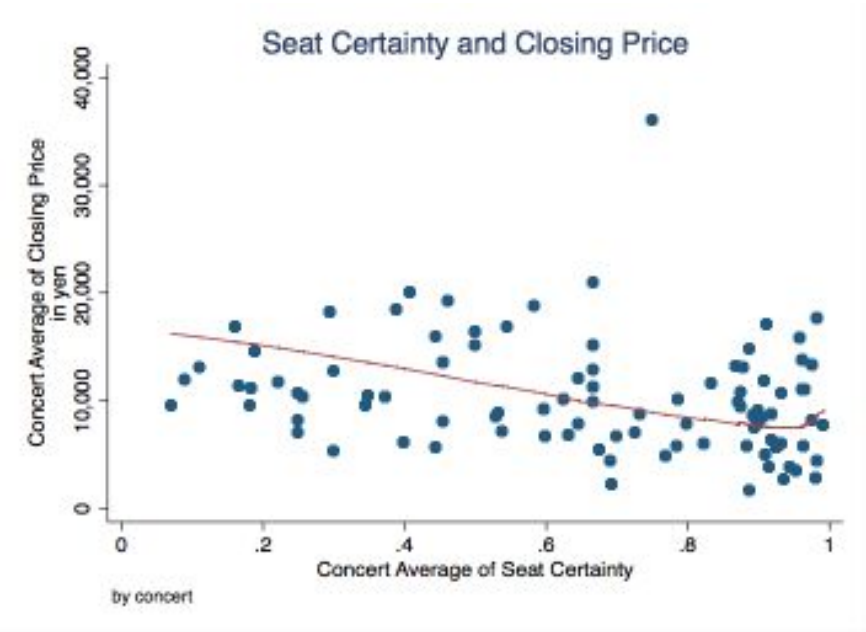


Figure 3-6: Days To Concert

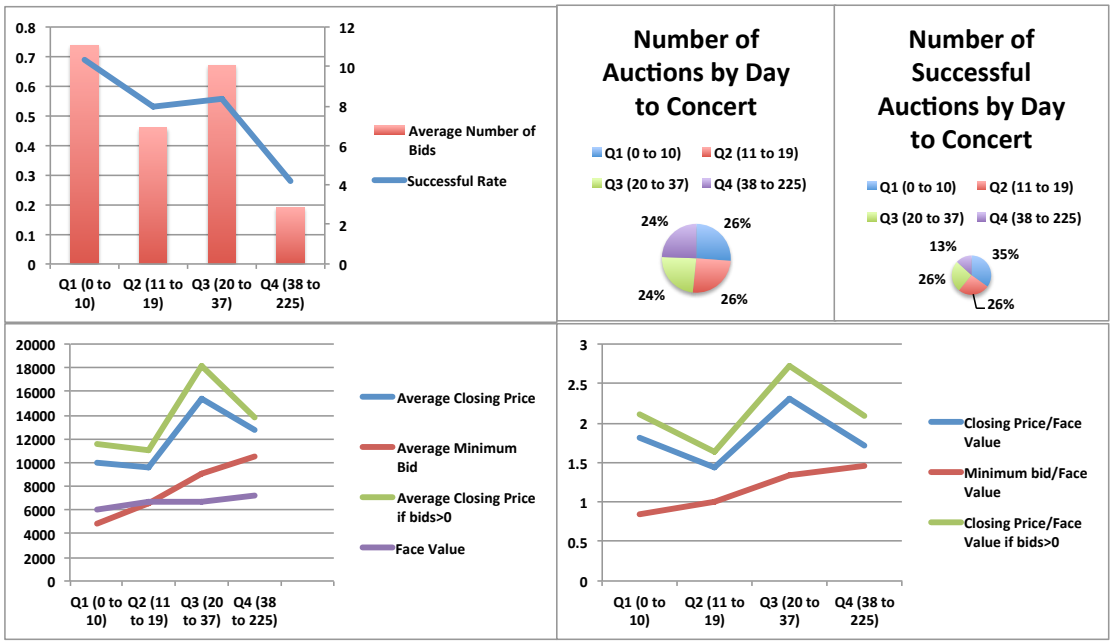


Figure 3-7 Seating Announcements

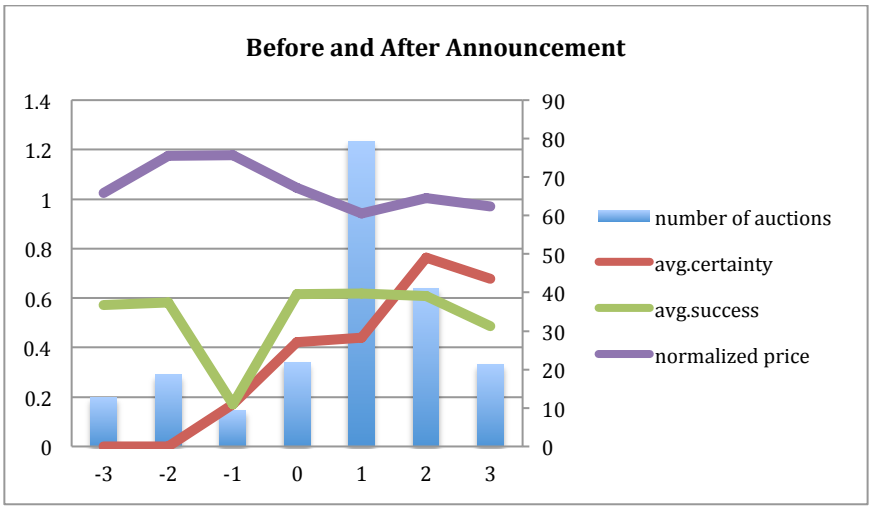


Figure 3-8: Evolution From Seating Announcement to Concert Date

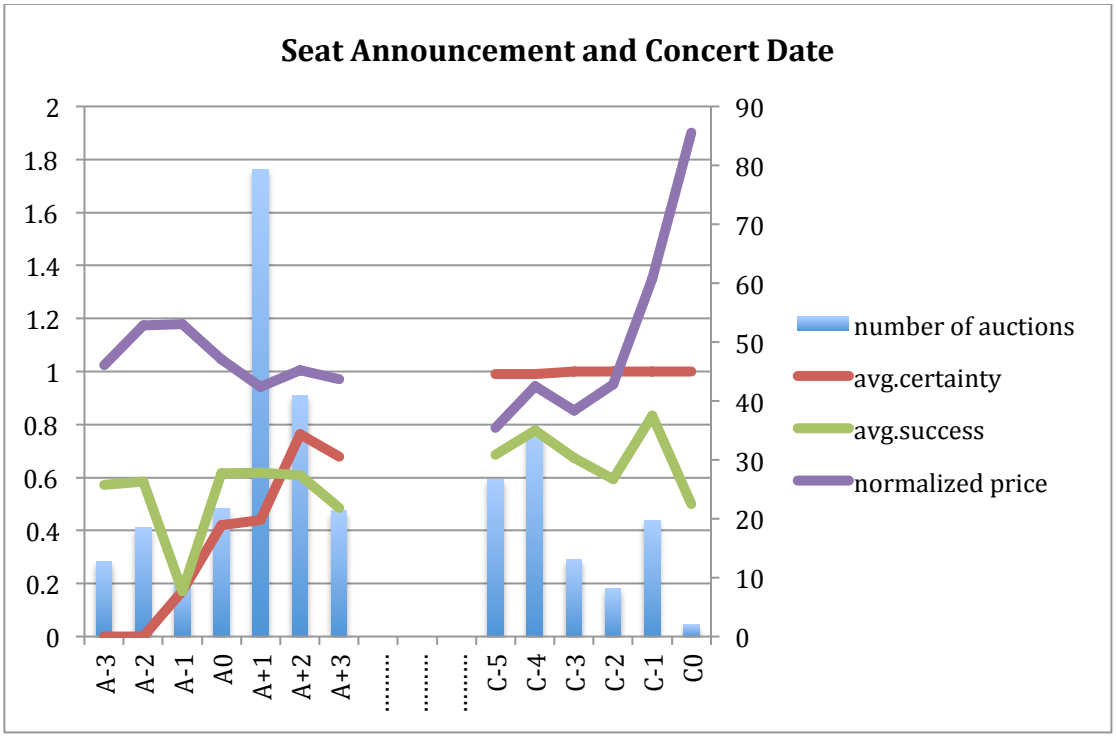


Figure 4-1: Features of Auctions In The Same GCA

Figure 4-2: Sample Division

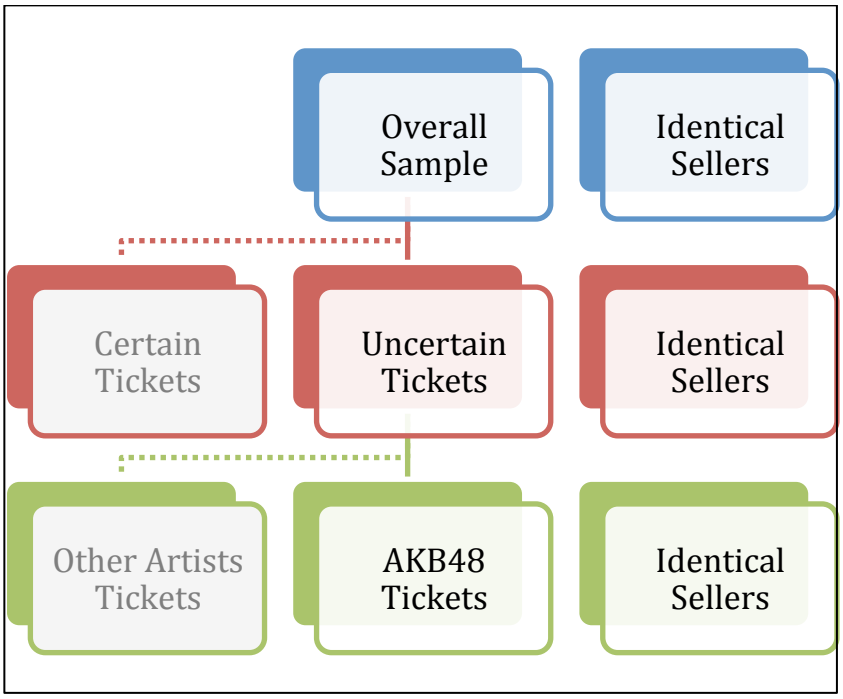


Figure 4-3: Missed Opportunity Across Sample Categories

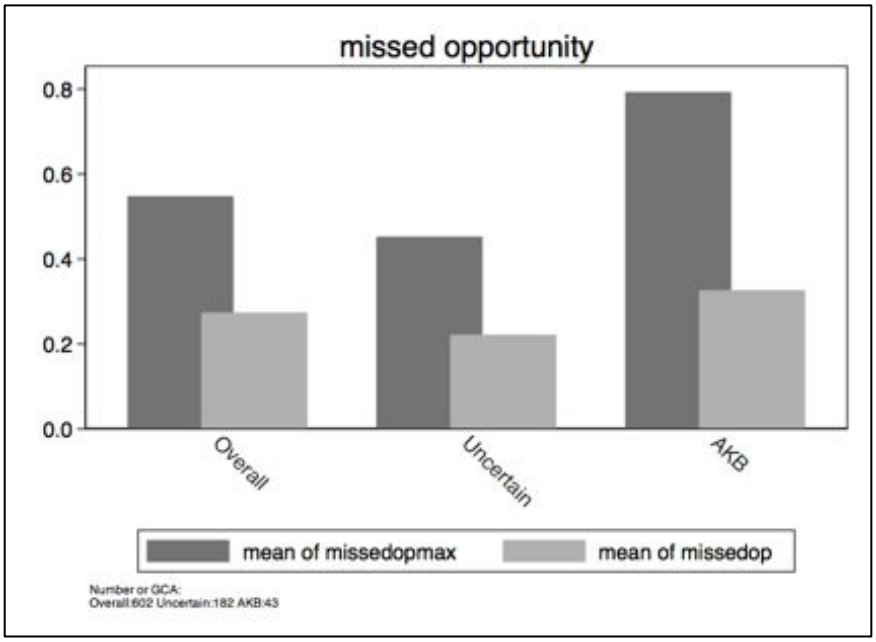


Figure 4-4: Missed Opportunity Across Sample Categories and GCA Size

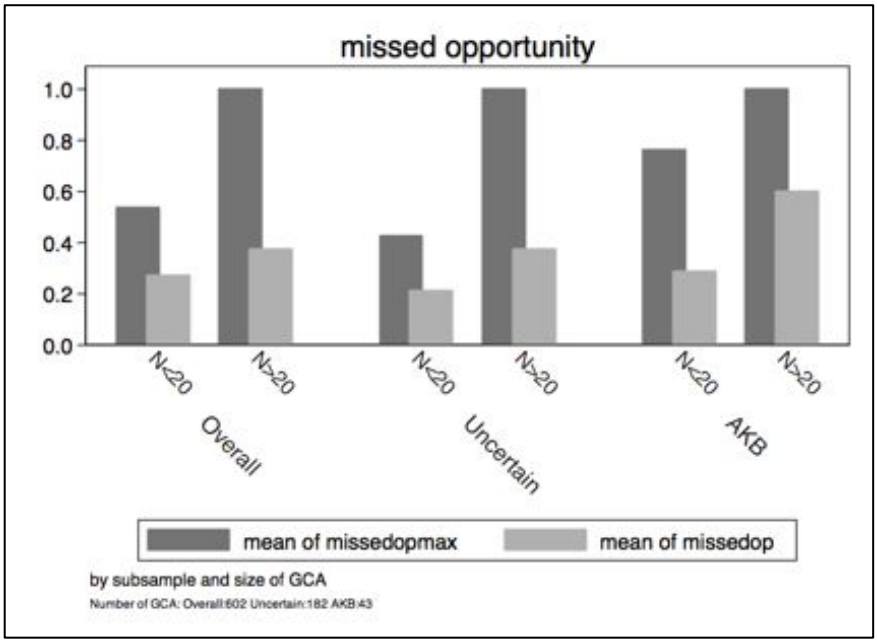


Figure 4-5: Missed Opportunity Across Sample Categories for Identical Seller

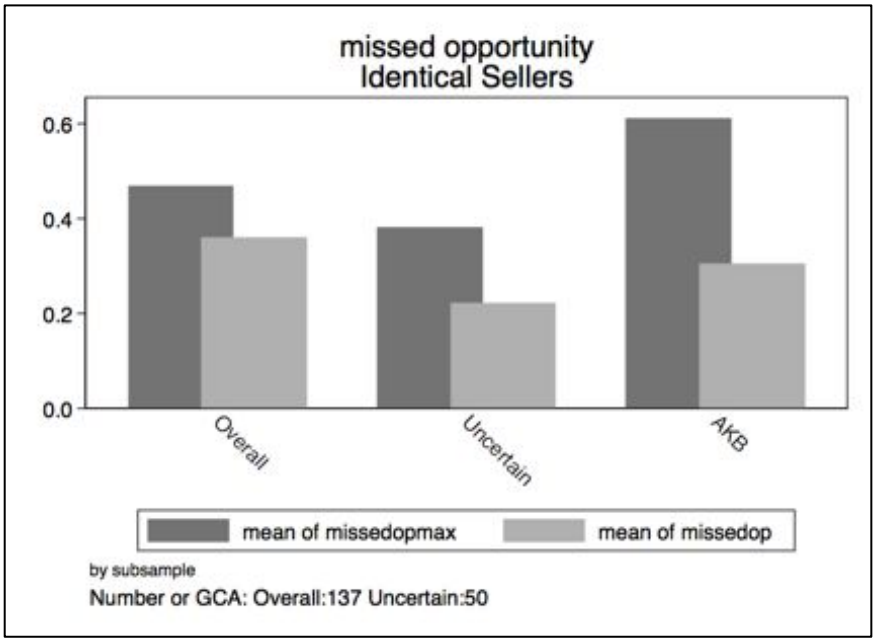


Figure 4-6: 'Uncertain' Errors

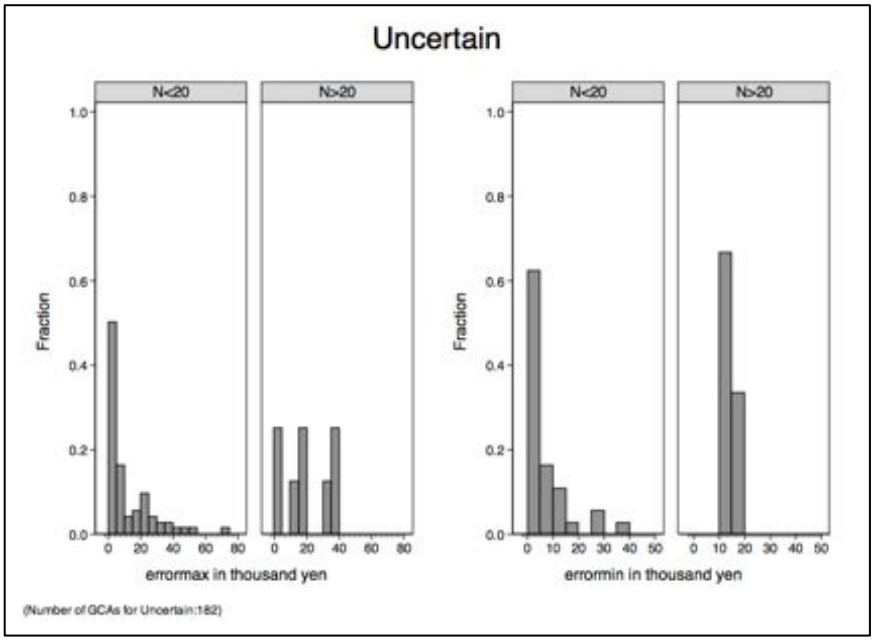


Figure 4-7: Overall Sample Errors

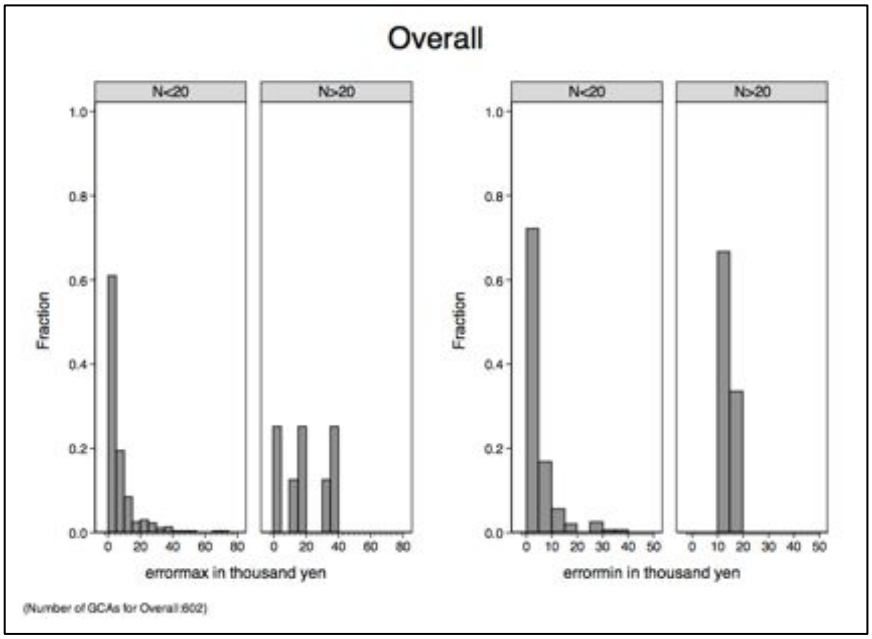


Figure 4-8: AKB48 Errors

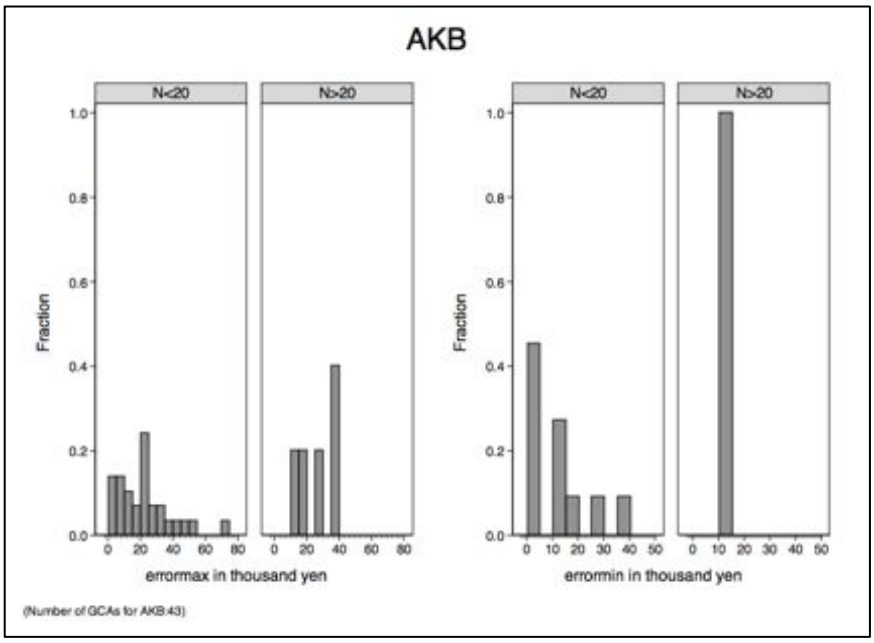


Figure 4-9: 'Uncertain' Errors for Identical Sellers

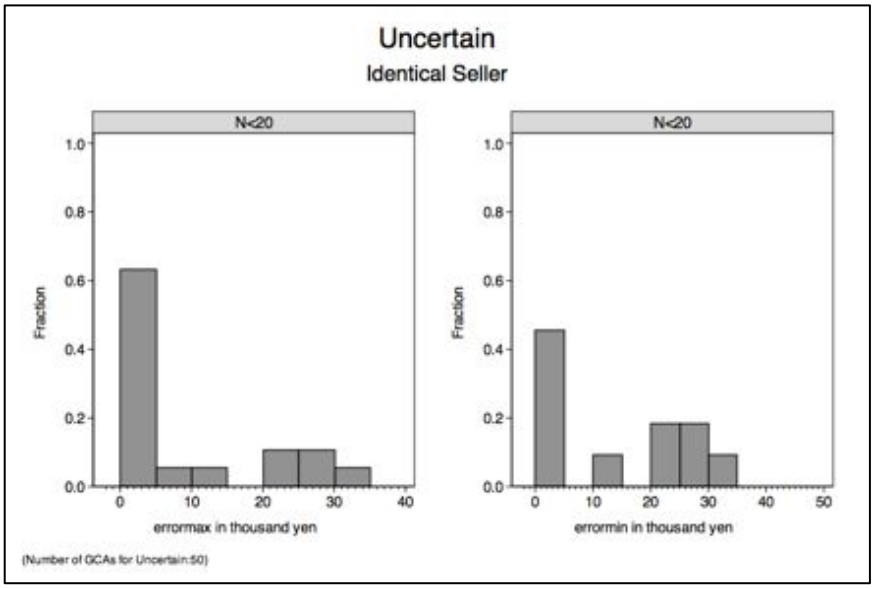


Figure 4-10: Overall Sample Errors for Identical Sellers

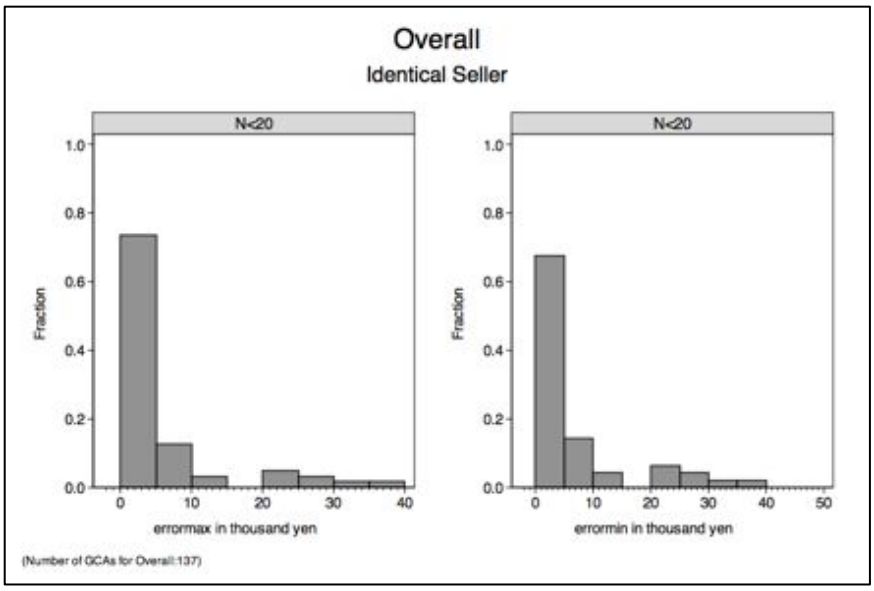


Figure 4-11: AKB48 Errors for Identical Sellers

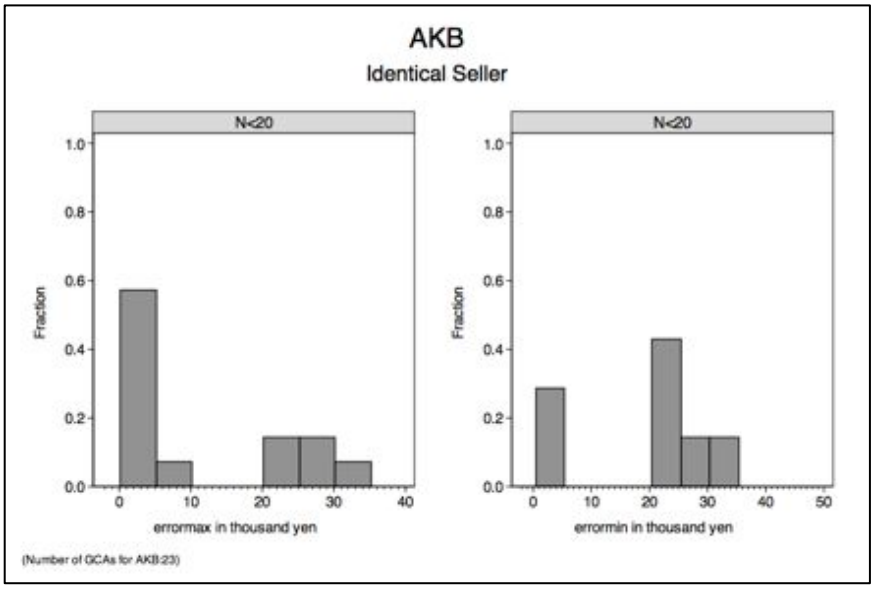


Figure 4-12: Errors Over Tickets' Minimum Reservation Price for Unsuccessful Auctions

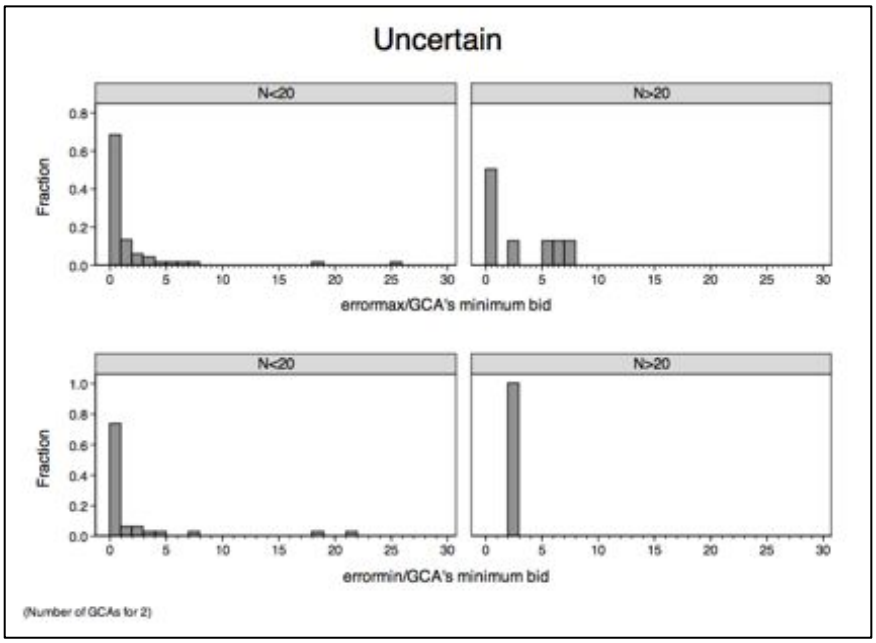


Figure 4-13: Errors Over Tickets' Face Value

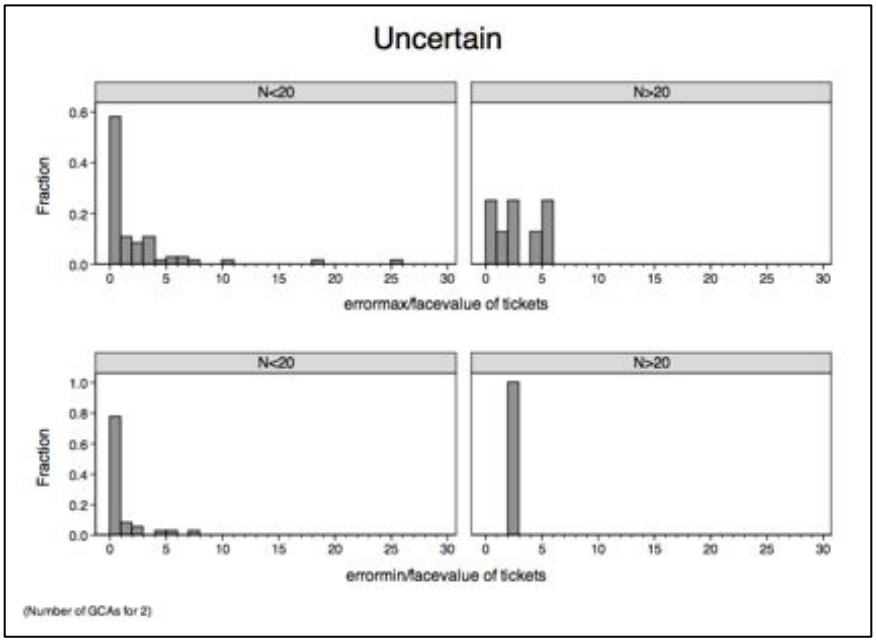


Figure4-14: Missed Opportunity by Seat Category

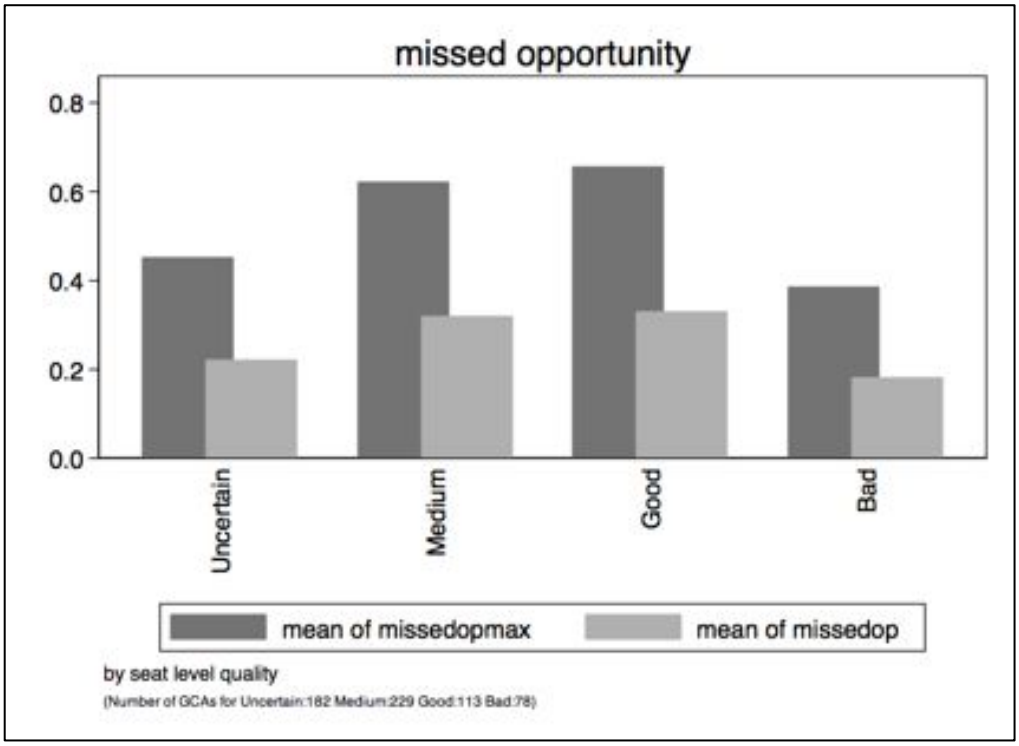


Figure 4-15: Errormax by Seat Category

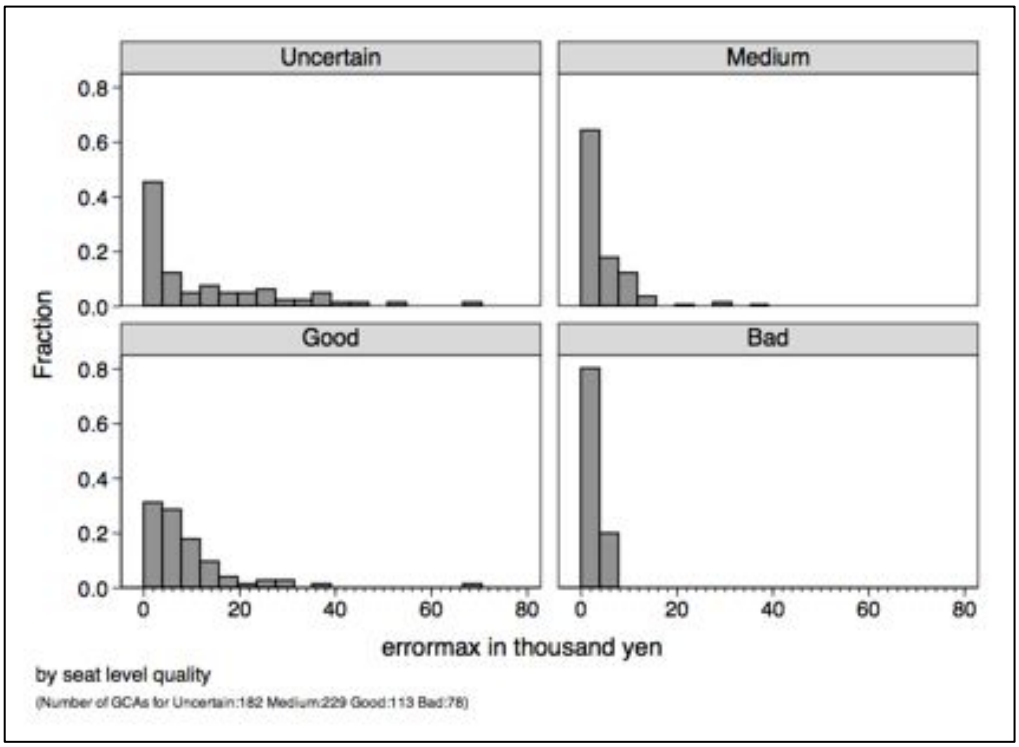


Figure 4-16: Errormin by Seat Category

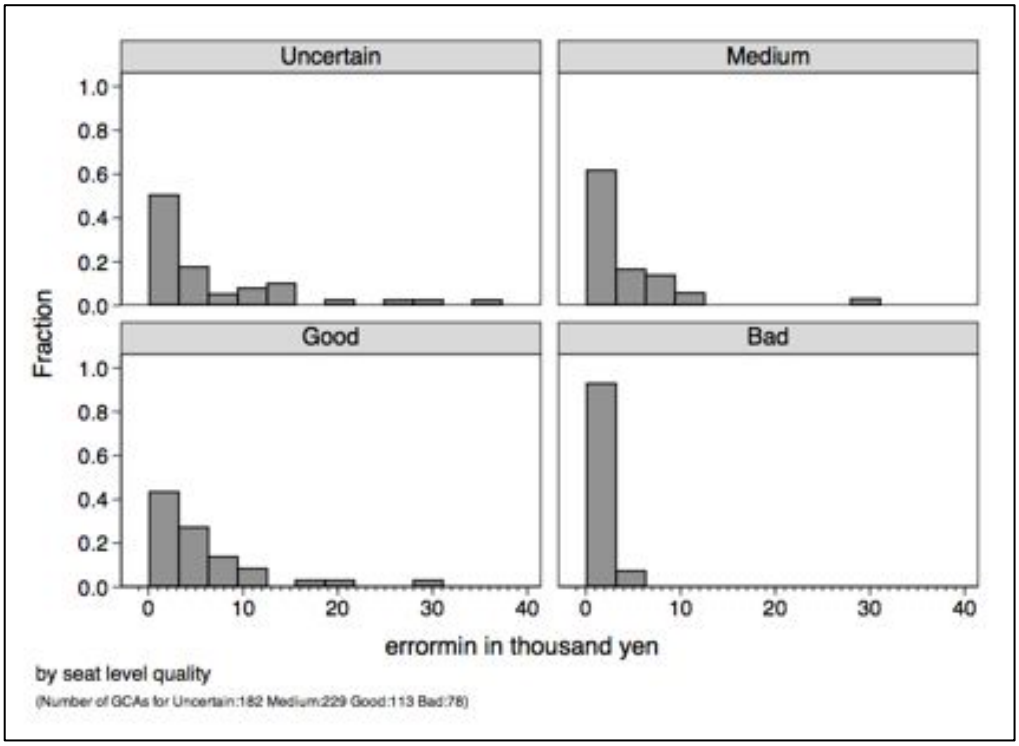


Figure 4-17: Missed Opportunities Assuming Bidders Ignoring Small Errors

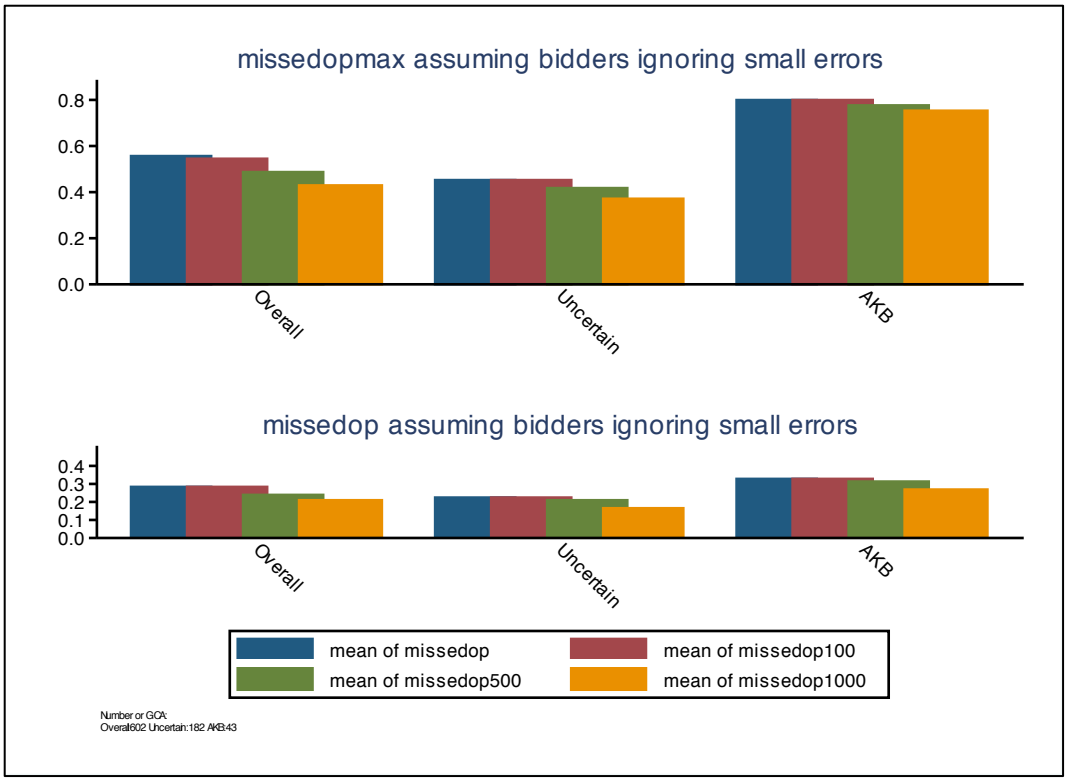


Figure 4-18: Competitive Arousal Average Bids and Errors

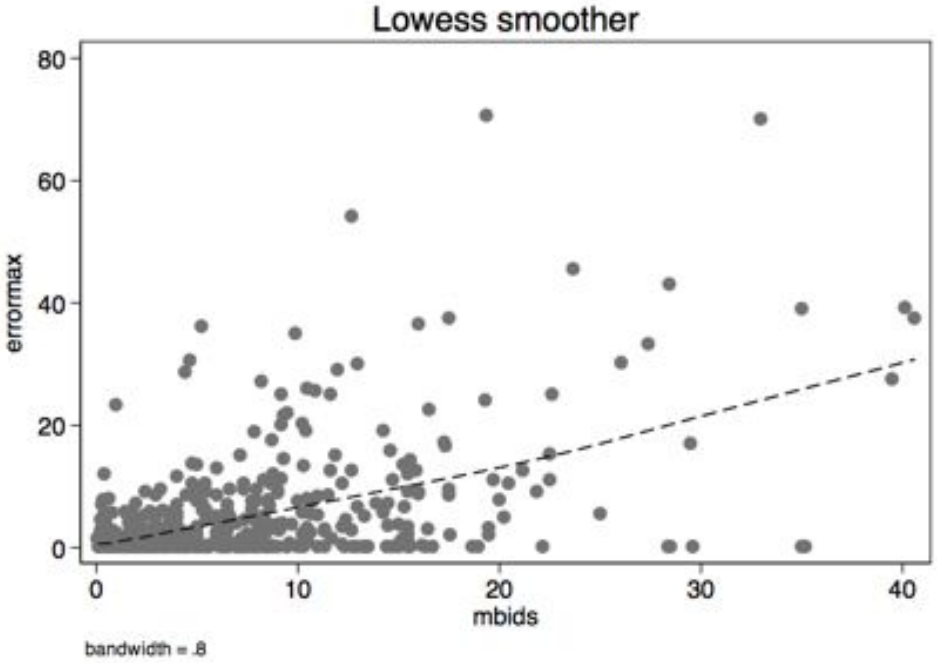
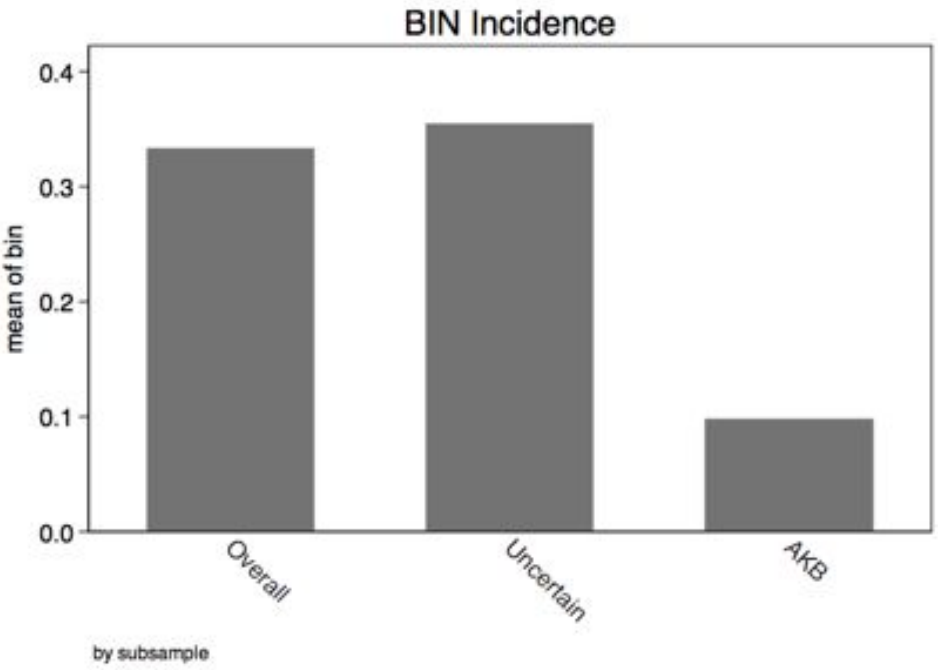


Figure 4-19 BIN Across Sample



APPENDIX

Table 2A-1: Yahoo Japan Auction Minimum Bid Increments

Current Price	Minimum Bid Increment
￥１−￥１,０００	￥１０
￥１,０００−￥５,０００	￥１００
￥５,０００−￥１０,０００	￥２５０
￥１０.０００−￥５０,０００	￥５００
￥５０,０００−	￥１,０００

Source: Yahoo Japan Auction, Retrieved December 22, 2014 from http://www.yahoo-help.jp/app/answers/detail/p/353/a_id/40661

Figure 2A-1: **Price Discriminated Concert Tickets**

Source: Ticket Pia, Retrieved September 6, 2013 from http://ticket.pia.jp/pia/event.do?eventCd=1213898

Figure 2A-2: Full Lottery Concert Application for Fan-club Members

NEWS DOME CONCERT 2010

(FC会員チケット代金) / 1枚 6,500円 〈 〉 [申込締切] 8月6日(金)

◆公演スケジュール

会場	公演日	開演時間	公演コード
京セラドーム大阪	9月19日(土)	18:00	09191N
	9月20日(日)	16:00	09201N
東京ドーム	9月25日(土)	18:30	09251N
	9月26日(日)	18:30	09261N
	9月27日(月)	18:30	09271N

お申込み方法

1 2 3 4

口座番号：00110-6-277759
加入者名：NEWSコンサート事務局

◆座席ブロックのご案内

◆車椅子席をご希望の方へ

＜お申込み方法のなかれ＞

0570-000-058

東京都渋谷区：〒107-8350 コンサート事務局「NEWS ドームコンサート 2010」チケット問合せ係

Figure 2A-3: Fanclub Lottery Application Period and Result Announcement for Lottery with General Release Concert

Source: http://www.kimhyungjun.jp/event/2012_zepp_tour/ Retrieved September 6, 2013

Figure 2A-4: Ticket Agency Lottery Application Period and General Release for Lottery with General Release Concert

Source: Ticket Pia, Retrieved September 6, 2013 from http://ticket.pia.jp/pia/event.do?eventCd=1225635

Figure 2A-5: List of Artist with Biggest Concert Mobilization in the First Half of 2013

2/3/2014 Nihon Keizai Shimbun

2013年コンサートの観客動員数が最も多いのは？

動員数ランキング TOP50

順位	アーティスト名	動員数(万人)	公演数	コンサートの内容
1	EXILE	112.4	23	「フラッグ」を振ってライブを応援するのがファンの間でのルール。最新シングル(Flower Song)も好調。
2	東方神起	89.3	18	ライブは構成も良く、終りに繰られる演出が人気。ファン層も幅広く、子ども中心配置も会場に多く見られる。
3	関ジャニ∞	78.5	40	トークやコントで笑いをとり、バンド構成で盛り上げる。エンタテインメント満載のライブが人気。
4	嵐	78.3	24	コンサートの演出に関しては「ライブ番長」と言われる演出家として細部にまでこだわりを見せている。
5	BIGBANG	71.9	15	ステージには相当にこだわっており、昨年のワールドツアーでは、レディー・ガガの演出家とタッグを組んだ。
6	Mr.Children	69.3	40	ライブは曲を中心とした構成となっている。今年は夏フェスのGRAMMY-ソングにも出演が決まっている。
7	ゆず	68.7	48	6月15日の北海道公演を皮切りに、9月の横浜ホールまで3カ月にわたるアリーナツアーを行っている。
8	AKB48	67.6	189	夏の5大ドームツアーのラストは東京ドーム連続4デイズ。7月の札幌ドームでは、元AKB48前田敦子が出演予定。
9	B'z	59.1	30	今年デビュー25周年を迎える。6月からは全国30公演のツアーを開催中。タイトルはSINGLESS SUMMER。
10	Hey!Say!JUMP	40.7	25	5月12日の東京ドームでの最終公演には、メンバーが3階席に設けられたスカイステージで登場した。
11	GLAY	40.1	25	今回のツアーはニューアルバムからの新曲中心の構成。
12	V6	39.1	16	2月発売のアルバム「Oh! My! Goodness!」のツアー。
13	FUNKY MONKEY BABYS	39.0	23	惜しまれながら6月に東京ドームで解散ライブ「3DAYS」。
14	ケツメイシ	37.6	30	ライブツアーは沖縄でファイナルを迎えるのが定番。
15	少女時代	36.8	20	1年7カ月ぶりとなるジャパンツアーで7都市をまわる。
16	浜崎あゆみ	36.6	28	デビュー15周年を記念した、全国のアリーナツアー。
17	G-DRAGON	36.1	8	クリスタルのレーシングカーで登場など演出も豪華。
18	安室奈美恵	32.4	43	7月発売のアルバム「FEEL」のツアーは4カ月に及ぶ。
19	ももいろクローバーZ	29.7	15	8月に日産スタジアムで7万人を集めるライブを予定。
20	いきものがかり	28.7	25	全国13カ所26公演のツアーで28万人を動員予定。
21	2PM	28.3	14	日本デビューから2年で念願の東京ドーム公演を開催。
22	倖田來未	26.7	16	最終形となるツアー「JAPONESQUE」を6都市で開催。
23	Kis-My-Ft2	25.3	18	大阪城ホールを皮切りに全国ツアー6都市18公演。
24	Sexy Zone	25.2	21	この春に6都市を回る初の全国ツアーを行った。
25	コブクロ	24.7	9	昨年の休養宣言後、初となるツアーを実施。
26	氷川きよし	24.6	125	1月から11月までの大型ツアーで全国をまわる。
27	Superfly	24.0	44	昨年デビュー5周年を迎え全国でホールツアーを開催。
28	さだまさし	23.1	95	年間100本以上のライブは当たり前で、最高は162本。
29	SHINee	22.9	17	ツアーのチケットには会場限定のペンライト付き。
30	AAA	22.8	41	ライブではアクロバットや演劇を披露する場面も。
31	KinKi Kids	22.0	4	東京ドーム単独アーティスト最多記録を4回に更新。
32	NEWS	21.2	14	今年のツアーも昨年同様、野外のライブ会場あり。
33	DREAMS COME TRUE	19.1	14	今年は「夢ワン」と呼ばれるマニアックな曲中心の演出。
34	BUMP OF CHICKEN	17.9	12	8月9日には、7月に発売したベストアルバム記念公演を。
35	バックストリート・ボーイズ	17.3	10	結成20周年を迎え、オリジナルメンバー5人での来日。
36	FTISLAND	16.8	11	3rdアルバム「RATED-FT」を引っさげての大型ツアー。
37	JUJU	16.3	40	昨年リリースした2枚のベストアルバムの記念ツアー。
38	湘南乃風	16.0	21	8月に横浜スタジアムで10周年記念ライブを開催。
39	矢沢永吉	15.7	14	11月から、5月に発売したベストアルバムツアーを行う。
40	SUPER JUNIOR	15.3	5	7月に今年で結成を迎えるSUPER SHOWを開催。
41	スキマスイッチ	14.9	56	セルフカバーアルバムを持って47都市等ツアーを開催。
42	ONE OK ROCK	13.7	11	キャリア史上最大のアリーナツアー11公演を行った。
43	ナオト・インティライミ	13.7	30	9月から11月にかけてアリーナツアーで6都市をまわる。

http://www.nikkei.com/news/image-article/?R_FLG=0&ad=DSXZZO5936531006092013000000&bf=0&dc=1&ng=DGXNASFK05027_V00C13A9000000&… 1/2

Source: Nihon Keizai Shinbum, Retrieved from http://www.nikkei.com/news

Figure 2A-6: Top 10 Record Companies Based on Record Sales

■2012年音楽ソフト市場「メーカー別シェア」TOP10

順位	メーカー（発売元）	売上金額		
		売上金額（億円）	占有率	前年比
1	エイベックス・グループ・ホールディングス	48,663.6	14.9%	116.8%
2	ソニー・ミュージックエンタテインメント	47,201.5	14.4%	91.0%
3	ユニバーサルミュージック	30,922.7	9.5%	85.0%
4	キングレコード	23,038.8	7.0%	100.5%
5	ジェイ・ストーム	17,795.8	5.4%	94.2%
6	EMIミュージック・ジャパン	17,042.3	5.2%	121.7%
7	ワーナーミュージック・ジャパン	16,178.5	4.9%	137.9%
8	ビクターエンタテインメント	15,206.6	4.6%	112.1%
9	トイズファクトリー	14,610.4	4.5%	216.7%
10	ポニーキャニオン	7,663.0	2.3%	82.9%

※対前年比は52週分（2012年）対53週分（2011年）で算出
集計期間：2012年1月2日～2012年12月30日

Source: Oricon, Retrieved October 8, 2013 from www.oricon.co.jp

Figure 2A-7: Johnny's Entertainment's and Pia Ticket Agency's Policy Regarding Ticket Resale

Article 5 (Prohibitions)

1. If any of the following are judged to be true of a Ticket Purchaser, the Company shall, on its own judgment, prohibit all ticket sales to said Ticket Purchaser. Tickets already sent to such Ticket Purchasers shall be invalid; already paid ticket fees shall not be refundable, and such Ticket Purchasers shall be denied entry to concert and performance venues. Such Ticket Purchasers found to have entered said venues shall be ejected.

(1). The Ticket Purchaser transfers tickets to a third party for the purpose of profit, or to a third party who has the purpose of making a profit, or is judged by the Company to have transferred tickets to a third party for the purpose of profit.

(2). The name given by the Ticket Purchaser is an alias or pseudonym.

(3). The address given by the Ticket Purchaser is different from the Ticket Purchaser's real address.

(4). The tickets held by a venue-goer were resold for the purpose of profit by online auction, scalper or the like.

(5). The tickets held by a venue-goer were purchased at a price higher than the sale price.

(6). The Ticket Purchaser has conducted photographic, video or audio recording at a concert or other performance (including by use of a mobile telephone).

(7). The Ticket Purchaser otherwise fails to follow the instructions of the sponsor at a concert or other performance.

(8). The Ticket Purchaser purchases illegally captured photographs or video at a concert or other performance.

(9). The Ticket Purchaser stalks or slanders a performer at a concert or other performance.

(10). The Ticket Purchaser troubles or harasses another venue-goer (if the Ticket Purchaser or a companion thereof violates various rules, or commits a related act, or causes loss to another venue-goer or a staff member, the Ticket Purchaser shall be responsible for compensation of damages.)

2. If the purchased tickets were resold through online auction or a scalper, or were otherwise resold by a third party for the purpose of profit, all tickets purchased by the Ticket Purchaser become invalid, and all ticket sales to the Ticket Purchaser may be prohibited from that time onward.

T09555445 0570-02-9999 http://pia.jp/t

Article 6 (Restrictions on Entry and Ejection from Venues)

If any of the following are judged to be true of a Ticket Purchaser, the Company may restrict the Ticket Purchaser's entry to concert or other performance venues, or may eject said Ticket Purchaser from a venue. In such cases ticket fees shall not be refundable.

1. The Ticket Purchaser refuses to present a fan club membership card and personal identification when asked to do so or the purpose of verifying that that the ticket belongs to the Ticket Purchaser.
2. The Ticket Purchaser brings a camera, video recorder, or other audio or video recording equipment into a concert or other performance venue.
3. The Ticket Purchaser has made recordings using a mobile telephone at a concert or other performance.
4. The Ticket Purchaser has purchased tickets under special conditions specified for a given performance, such as Parent-Child Seats, and the Ticket Purchaser is deemed not to satisfy these conditions.

Article 7 (Handling of Violations of the Agreement and Other Issues)

1. If the Ticket Purchaser is found to have committed scalping or other actions in violation of Metropolitan Tokyo's By-law on Prevention of Violent and Delinquent Acts and Other Gross Harassment of the Public, or similar by-laws of local governments, the Company has a duty to file a criminal complaint against the Ticket Purchaser with the competent authorities. "Scalping" is the act of reselling tickets to unspecified persons in a public place, or conveying tickets to persons who have the purpose of reselling them to unspecified persons in a public place.
2. If the Company recognizes a reasonable suspicion that the Ticket Purchaser has engaged in criminal, prohibited or other improper behavior, the Company may refuse to sell tickets to the Ticket Purchaser or may render any tickets already sold to the Ticket Purchaser invalid (without refund of the ticket fee). Such behavior includes but is not limited to the following examples.

(1). Multiple orders are received from the same address (other than from family and co-residents).

(2). Multiple orders are received from different names using the same handwriting

(3). The address given by the Ticket Purchaser is a business location of a company.

(4). Tickets purchased by the Ticket Purchaser are displayed on an online auction website (if only the seat numbers are displayed, all of the Ticket Purchasers for said seats are contacted for confirmation).

(5). Tickets purchased by the Ticket Purchaser are sold at a ticket shop (coupon shop, etc.).

If, as described above, an impropriety is discovered in tickets ordered by the Ticket Purchaser for persons other than the Ticket Purchaser, all tickets ordered by the Ticket Purchaser (including the Ticket Purchaser's ticket) may be rendered invalid. Ticket Purchasers are advised to ensure strictly that no tickets, including those of family and friends, may be resold.

The Company may disclose personal information in response to an official request from a court of law, police or similar public agency on the basis of law.

Source: Johnny's net, Retrieved October 7, 2013 from www.johnnys-net.jp

Figure 2A-8: Temporary Ticket with Partial Information of Seating Detail and Full Information Disclosed on Concert Date at Concert Venue

Figure 2A-9: The Use of Social Media to Exchange/ Barter Tickets

Source: Twitter, Retrieved October 18, 2013 from http://twitter.com

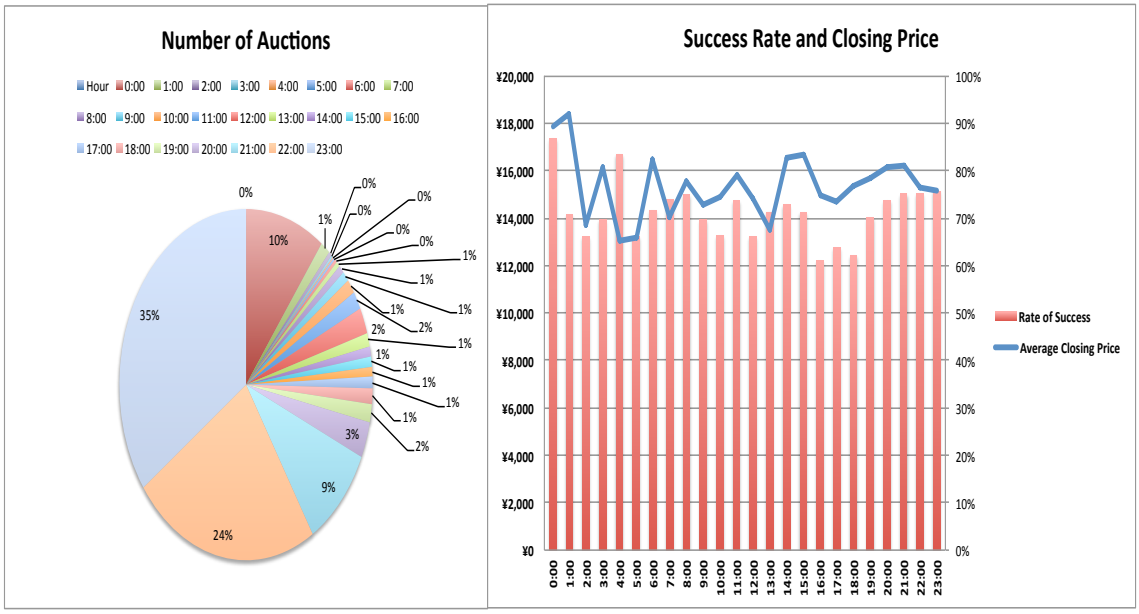
Figure 2A-10: Yahoo Auction Page (No Seating Details)

Source: Aucfan , retrieved December 24, 2014, from http://aucview/aucfan.com/yahoo/

Figure 2A-11: Retrieved Yahoo Auction Page with Seating Details Picture

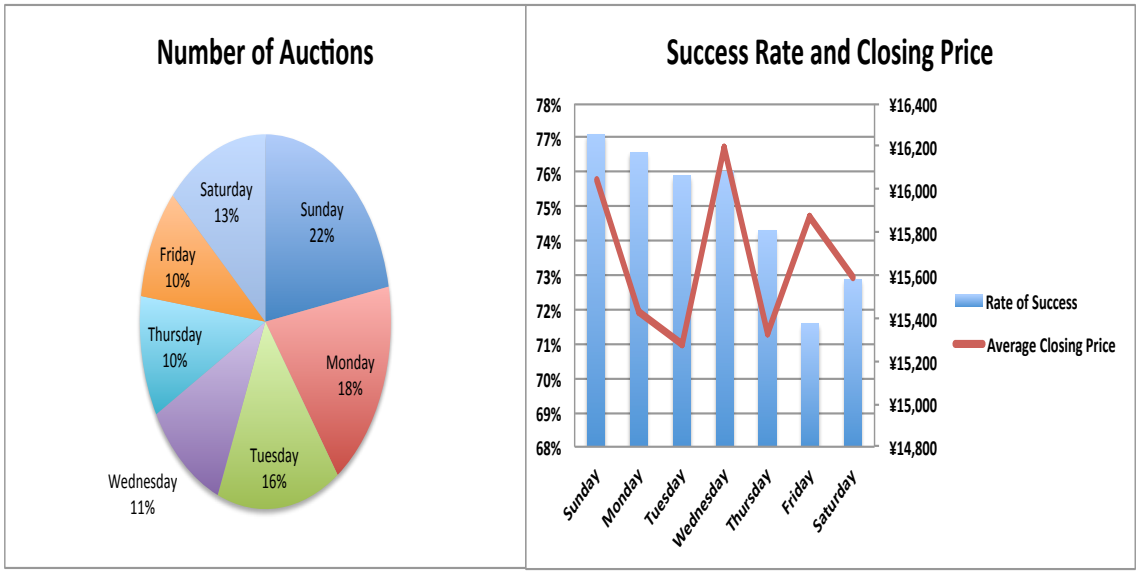
Source: Aucfan , retrieved December 24, 2014, from http://aucview/aucfan.com/yahoo/

Figure 2A-12: Yahoo Japan Auction Transactions by Hour of the Day July 2012



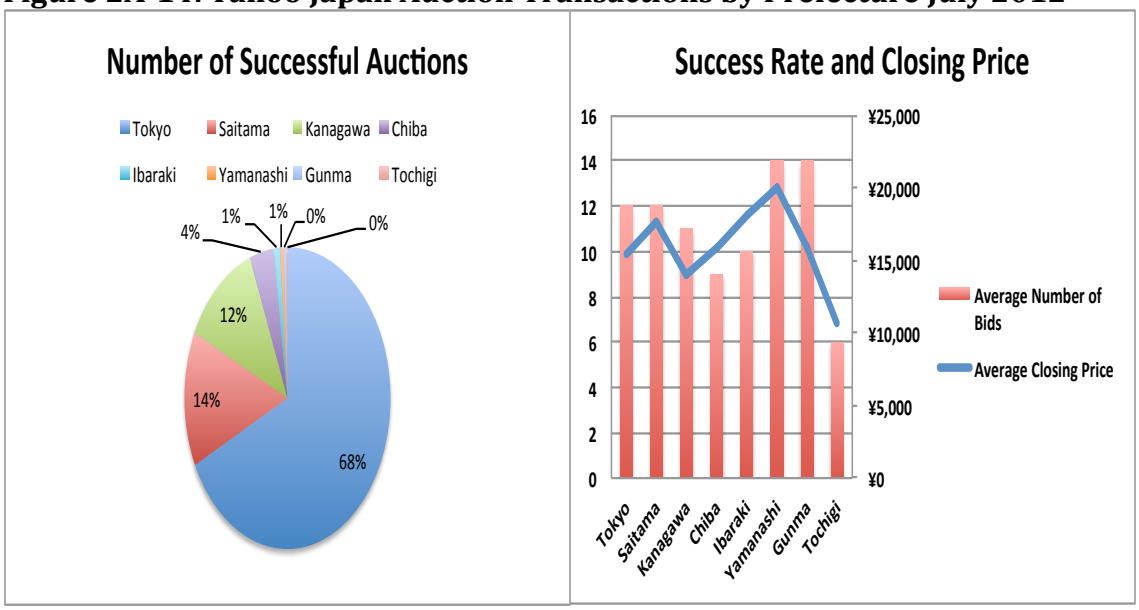
Source: Aucfan , retrieved October 2, 2013, from http://aucfan.com/yahoo

Figure 2A-13: Yahoo Japan Auction Transactions by Day of the Week July 2012



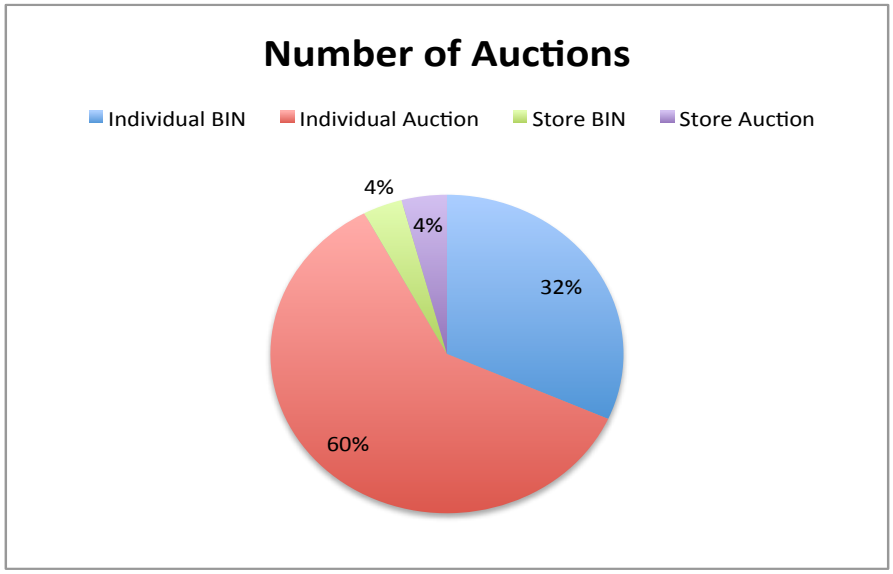
Source: Aucfan , retrieved October 2, 2013, from http://aucfan.com/yahoo

Figure 2A-14: Yahoo Japan Auction Transactions by Prefecture July 2012



Source: Aucfan , retrieved October 2, 2013, from http://aucfan.com/yahoo

Figure 2A-15: Yahoo Japan Auction Transactions by Seller Type July 2012



Source: Aucfan , retrieved October 2, 2013, from http://aucfan.com/yahoo

Table 3A-1: Sampling Schedule

	16th July	17th July	18th July	19th July	20th July	21th July	22nd July	23th July	24th July	25th July	26th July	27th July
	Mon	Tues	Wed	Thurs	Fri	Sat	Sun	Mon	Tues	Wed	Thurs	Fri
12am-2am												
2am-4am												
4am-6am												
6am-8am												
8am-10am												
10am-12pm												
12pm-2pm												
2pm-4pm												
4pm-6pm												
6pm-8pm												
8pm-10pm												
10pm-12am												

Table 3A-2: Baseline Results

	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regressions
	success	lnprice	success	lnprice
	(1)	(2)	(3)	(4)
Ln(minbid)	-0.05***	0.05**	-0.10***	0.06***
	[0.01]	[0.02]	[0.02]	[0.02]
exact	0.01	0.36***	0.05	0.46***
	[0.02]	[0.09]	[0.04]	[0.10]
exces	-0.16***	0.37***	-0.16***	0.49***
	[0.02]	[0.07]	[0.03]	[0.09]
Seat Certainty	0.14***	0.24***	0.18***	0.03
	[0.02]	[0.07]	[0.04]	[0.11]
Relative Quality	-0.29***	-1.63***	-0.36***	-1.38***
	[0.03]	[0.15]	[0.06]	[0.16]
Ln(compet)	0.01	-0.04	0.01	-0.03
	[0.01]	[0.03]	[0.02]	[0.04]
paired	-0.07***	-0.19**	-0.12***	-0.19**
	[0.02]	[0.08]	[0.03]	[0.08]
Ln(Feedback)	0.01**	-0.02	0.01	-0.04*
	[0.01]	[0.02]	[0.01]	[0.02]
feedzero	0.21***	-0.28*	0.25***	-0.44***
	[0.06]	[0.15]	[0.09]	[0.16]
feed100	0.05**	-0.03	0.06*	-0.08
	[0.02]	[0.06]	[0.04]	[0.07]
Ln(dtc)	-0.07**	0.14	-0.05	0.02
	[0.03]	[0.10]	[0.04]	[0.08]
dd1	-0.04	-0.47	-0.11	-0.16
	[0.06]	[0.29]	[0.10]	[0.21]
dd2	-0.02	-0.53*	-0.08	-0.21
	[0.05]	[0.26]	[0.08]	[0.18]
dd3	0.02	-0.38	-0.02	-0.04
	[0.05]	[0.26]	[0.06]	[0.16]
Peak Time	0.08*	0.22**	0.14**	0.21**
	[0.04]	[0.09]	[0.06]	[0.09]

Saturday	-0.05***	0.01	-0.08***	0.06
	[0.02]	[0.05]	[0.02]	[0.06]
Sunday	-0.02	-0.11	-0.03	-0.13*
	[0.03]	[0.07]	[0.04]	[0.07]
reselln	-0.09***	-0.09***	-0.17***	-0.15***
	[0.01]	[0.02]	[0.01]	[0.02]
BIN	-0.12***	-0.04	-0.17***	-0.08*
	[0.01]	[0.04]	[0.02]	[0.04]
Ln(FV)			0	0.32**
			[0.08]	[0.16]
mfloor			-0.02	0.13
			[0.08]	[0.19]
Tokyo			-0.02	0.11
			[0.06]	[0.17]
Full Lottery			0.09	1.02***
			[0.10]	[0.32]
hits			0.17**	0.94***
			[0.07]	[0.25]
superstar			-0.13***	-0.25*
			[0.04]	[0.13]
Band Festival			0.13*	0.05
			[0.07]	[0.20]
Solo			0.09	0.34**
			[0.06]	[0.16]
mrecord			-0.04	-0.05
			[0.08]	[0.19]
bigrecord			-0.22***	-0.33*
			[0.08]	[0.18]
multimana			-0.48***	-0.89***
			[0.07]	[0.18]
bigmana			-0.11*	-0.11
			[0.06]	[0.16]
bigprom			-0.13**	-0.36***
			[0.06]	[0.13]
Fstatistics	70	20.59		.
Adjusted R-square	0.27	0.3		.
Chi-square	.	.		1079.78

Chi-square p value	.	.	0.00
Log pseudo-likelihood	-2036.44	-2140.24	-4200
N	4826	2278	4530
Group Number	119	73	103
Group Max	431	344	.
Group Min	8	7	.
Overall R-square	0.28	0.12	

* $p<0.1$; ** $p<0.05$; *** $p<0.01$,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3A-3: Top Traded Concert

	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regressions
	success	lnprice	success	lnprice
	(1)	(2)	(3)	(4)
ln(minbid)	-0.06***	0.08***	-0.14***	0.08***
	[0.01]	[0.02]	[0.02]	[0.02]
exces	-0.15***	0.19***	-0.19***	0.26***
	[0.02]	[0.06]	[0.04]	[0.09]
Seat Certainty	0.14***	0.37***	0.28***	0.30***
	[0.03]	[0.05]	[0.05]	[0.06]
Relative Quality	-0.30***	-1.81***	-0.44***	-1.68***
	[0.04]	[0.18]	[0.06]	[0.19]
Ln(compet)	0.01	-0.06	-0.06**	-0.10**
	[0.01]	[0.04]	[0.02]	[0.05]
paired	-0.07**	-0.18*	-0.11**	-0.16
	[0.03]	[0.11]	[0.05]	[0.10]
Ln(Feedback)	0.01**	-0.03**	0.01**	-0.03**
	[0.00]	[0.01]	[0.01]	[0.02]
feedzero	0.17***	-0.26*		
	[0.05]	[0.13]		
Ln(dtc)	-0.07*	0.2	-0.02	0.08
	[0.04]	[0.17]	[0.03]	[0.07]
dd1	-0.12	-0.25		
	[0.08]	[0.33]		
dd2	-0.08	-0.28		
	[0.07]	[0.29]		
dd3	-0.01	-0.13		
	[0.07]	[0.27]		
Peak Time	0.11***	0.27**	0.31***	0.35***
	[0.04]	[0.10]	[0.07]	[0.12]
BIN	-0.12***	-0.02	-0.16***	-0.03
	[0.01]	[0.05]	[0.02]	[0.05]
reselln	-0.09***	-0.12***	-0.18***	-0.16***
	[0.01]	[0.03]	[0.01]	[0.03]

Ln(FV)			-0.15*	0.12
			[0.08]	[0.26]
mrecord			-0.59***	-0.68***
			[0.09]	[0.18]
bigrecord			-0.70***	-0.81***
			[0.05]	[0.10]
multimana			-0.41***	-1.12***
			[0.05]	[0.16]
Saturday			-0.09***	0.05
			[0.03]	[0.07]
Sunday			0	
			[0.04]	
Fstatistics	112.23	23.88		.
Adjusted R-square	0.31	0.31		.
Log pseudo-likelihood	-1426.73	-1765.07		-3314.39
Overall R-square	0.29	0.09		
N	3509	1748		3509
Group Number	47	41		47
Group Max	431	344		.
Group Min	10	8		.

* $p<0.1$; ** $p<0.05$; *** $p<0.01$,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3A-4: Cluster Averages as Controls

	Baseline		Group Averages Control	
	Probit	Truncated Regression	Probit	Truncated Regression
	success	lnprice	success	lnprice
	(1)	(2)	(3)	(4)
Ln(minbid)	-0.10***	0.06***	-0.10***	0.05***
	[0.02]	[0.02]	[0.02]	[0.02]
exact	0.05	0.47***	0.01	0.35***
	[0.04]	[0.10]	[0.04]	[0.09]
exces	-0.16***	0.52***	-0.24***	0.37***
	[0.03]	[0.09]	[0.03]	[0.07]
Seat Certainty	0.17***	0.02	0.23***	0.22***
	[0.04]	[0.10]	[0.04]	[0.06]
Relative Quality	-0.36***	-1.33***	-0.45***	-1.57***
	[0.06]	[0.15]	[0.05]	[0.14]
Ln(compet)	0.01	-0.01	0	-0.04
	[0.02]	[0.03]	[0.02]	[0.03]
paired	-0.12***	-0.18**	-0.12***	-0.16**
	[0.03]	[0.07]	[0.03]	[0.07]
Ln(Feedback)	0.01	-0.04*	0.02***	-0.03
	[0.01]	[0.02]	[0.01]	[0.02]
feedzero	0.25***	-0.38**	0.29***	-0.33**
	[0.09]	[0.15]	[0.08]	[0.15]
feed100	0.06*	-0.09	0.08**	-0.04
	[0.04]	[0.07]	[0.04]	[0.06]
ln(dtc)	-0.05	-0.01	-0.08*	0.16
	[0.04]	[0.08]	[0.04]	[0.10]
dd1	-0.11	-0.2	-0.03	-0.37
	[0.10]	[0.20]	[0.10]	[0.25]
dd2	-0.08	-0.23	-0.03	-0.44*
	[0.08]	[0.16]	[0.10]	[0.23]
dd3	-0.02	-0.07	0.02	-0.31
	[0.06]	[0.14]	[0.09]	[0.22]
Peak Time	0.14**	0.17**	0.15**	0.21**
	[0.06]	[0.09]	[0.07]	[0.08]
Saturday	-0.08***	0.06	-0.10***	0.02
	[0.02]	[0.06]	[0.03]	[0.05]

Sunday	-0.03	-0.12*	-0.04	-0.1
	[0.04]	[0.06]	[0.04]	[0.06]
reselln	-0.17***	-0.13***	-0.15***	-0.07***
	[0.01]	[0.02]	[0.01]	[0.02]
BIN	-0.17***	-0.09**	-0.16***	-0.03
	[0.02]	[0.04]	[0.02]	[0.03]
Ln(FV)	0	0.40***	-0.01	0.42***
	[0.08]	[0.14]	[0.08]	[0.13]
mfloor	-0.02	-0.04	-0.1	-0.12
	[0.08]	[0.16]	[0.23]	[0.45]
Tokyo	-0.02	0.02	-0.01	0.21*
	[0.06]	[0.16]	[0.05]	[0.11]
Full Lottery	0.09	0.79**	0.07	0.54**
	[0.10]	[0.31]	[0.09]	[0.22]
hits	0.17**	0.65***	0.19***	0.66***
	[0.07]	[0.20]	[0.05]	[0.12]
superstar	-0.13***	-0.23*	-0.15***	-0.37***
	[0.04]	[0.12]	[0.04]	[0.12]
Band Festival	0.13*	-0.03	0.08	-0.12
	[0.07]	[0.14]	[0.07]	[0.14]
Solo	0.09	0.30*	0.12**	0.27***
	[0.06]	[0.16]	[0.05]	[0.10]
mrecord	-0.04	0	0.11	0.53***
	[0.08]	[0.17]	[0.09]	[0.15]
bigrecord	-0.22***	-0.25	-0.07	0.15
	[0.08]	[0.18]	[0.06]	[0.12]
multimana	-0.48***	-0.82***	-0.25***	-0.25
	[0.07]	[0.14]	[0.08]	[0.16]
bigmana	-0.11*	-0.18	-0.03	0.01
	[0.06]	[0.15]	[0.05]	[0.09]
bigprom	-0.13**	-0.24**	-0.10*	0
	[0.06]	[0.11]	[0.05]	[0.09]
grln(minbid)			0.05	0.14
			[0.05]	[0.10]
grexact			0.21	0.78**
			[0.18]	[0.33]
grexces			0.38***	0.61**
			[0.14]	[0.31]

grrel.quality			-0.01	0.53
			[0.55]	[1.07]
grgood2			-0.26	-0.99**
			[0.30]	[0.48]
grbad2			0.12	-0.2
			[0.22]	[0.44]
grmedcertain2			-0.2	-0.90***
			[0.14]	[0.28]
grlncompet			0.02	0.11**
			[0.03]	[0.05]
grpair			-0.11	-0.69**
			[0.13]	[0.29]
grln(dtc)			0.05	-0.1
			[0.10]	[0.21]
grdd1			-0.12	0.48
			[0.25]	[0.61]
grdd2			0	0.58
			[0.18]	[0.44]
grdd3			-0.08	0.45
			[0.13]	[0.38]
grslots2			-0.17	-1.46*
			[0.42]	[0.75]
grln(feedback)			-0.13***	-0.24***
			[0.04]	[0.07]
grfeedzero			-0.29	3.04
			[1.37]	[2.57]
grfeed100			-0.23	-1.08***
			[0.19]	[0.38]
grbin			-0.1	-0.76***
			[0.12]	[0.23]
grSaturday			-0.12	0.06
			[0.20]	[0.42]
grSunday			0.03	-0.93**
			[0.24]	[0.42]
grreselln			-0.27***	-0.46***
			[0.05]	[0.11]
Chi-square	941.29	1415.19	3330.90	4035.61
N	4826	2440	4826	2440

Number of Cluster	.	112	.	112

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 ,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Table 3A-5: Announcement and Seat Certainty

	Pre-announcement	Post-announcement	Total
Uncertain Seat Quality	355	473	828
Certain Seat Quality	93	2588	2,681
Total	448	3061	3509

Table 3A-6: Announcement and Seat Quality

	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regression	Linear Panel Regression with Fixed Effects	Linear Panel Regression with Fixed Effects	Probit	Truncated Regression
	success	ln(price)	success	ln(price)	success	ln(price)	success	ln(price)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good	0.20***	0.49***	0.25***	0.24	0.20***	0.41**	0.27***	0.19
	[0.07]	[0.18]	[0.08]	[0.15]	[0.07]	[0.19]	[0.08]	[0.16]
Bad	0.08	0.25	0.25***	0.38**	0.08	0.19	0.27***	0.34**
	[0.05]	[0.18]	[0.08]	[0.15]	[0.05]	[0.17]	[0.08]	[0.16]
Medium	0.17***	0.23**	0.29***	0.19**	0.18***	0.16*	0.31***	0.14
	[0.04]	[0.10]	[0.06]	[0.09]	[0.04]	[0.08]	[0.06]	[0.09]
pre-announcement					0.02	-0.14**	0.05	-0.09***
					[0.03]	[0.07]	[0.05]	[0.03]
Relative Quality	-0.13	-1.50***	-0.44**	-1.94***	-0.13	-1.54***	-0.44**	-1.95***
	[0.16]	[0.53]	[0.18]	[0.38]	[0.16]	[0.53]	[0.18]	[0.38]

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 ,clustered s.e in the brackets, Marginal Effect at the Means are substituted for Probit estimates

Figure 3A-1: Distribution of Price Variables

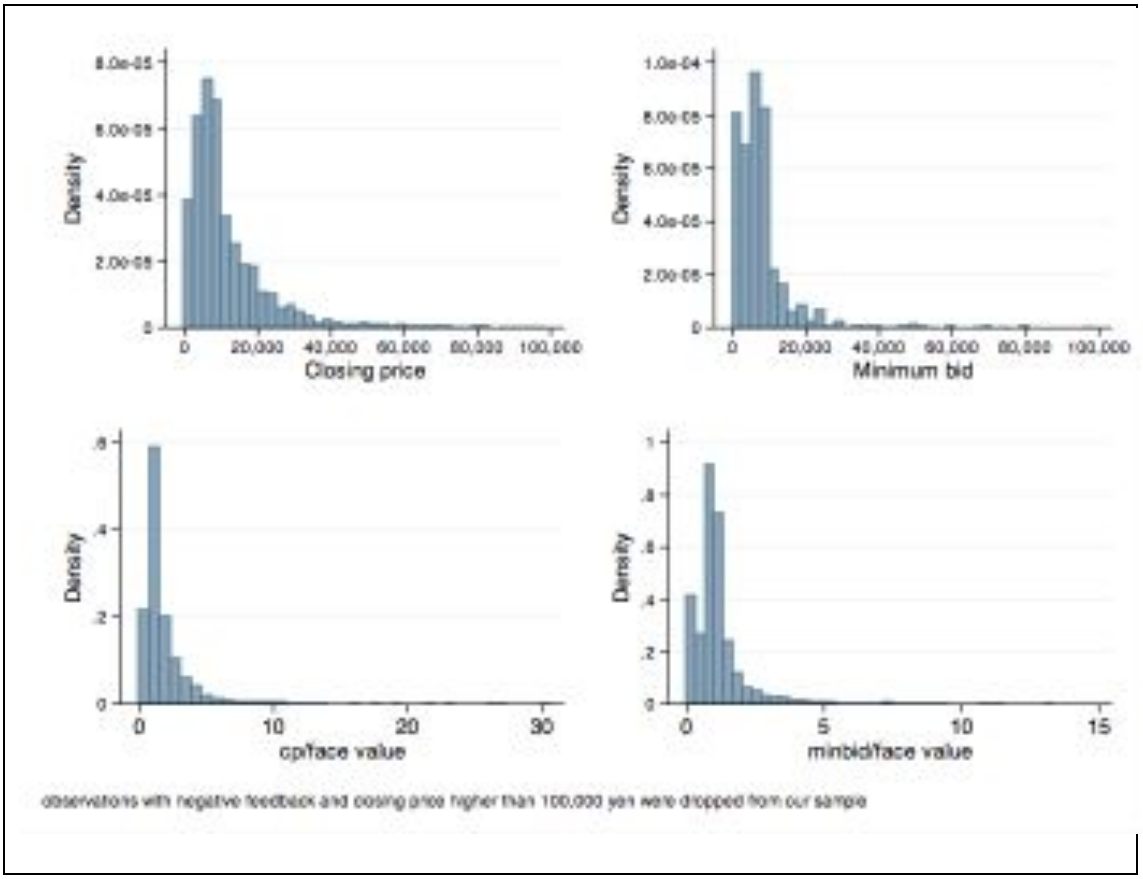


Figure 3A-2: Distribution of Price Variables in Natural Logarithm

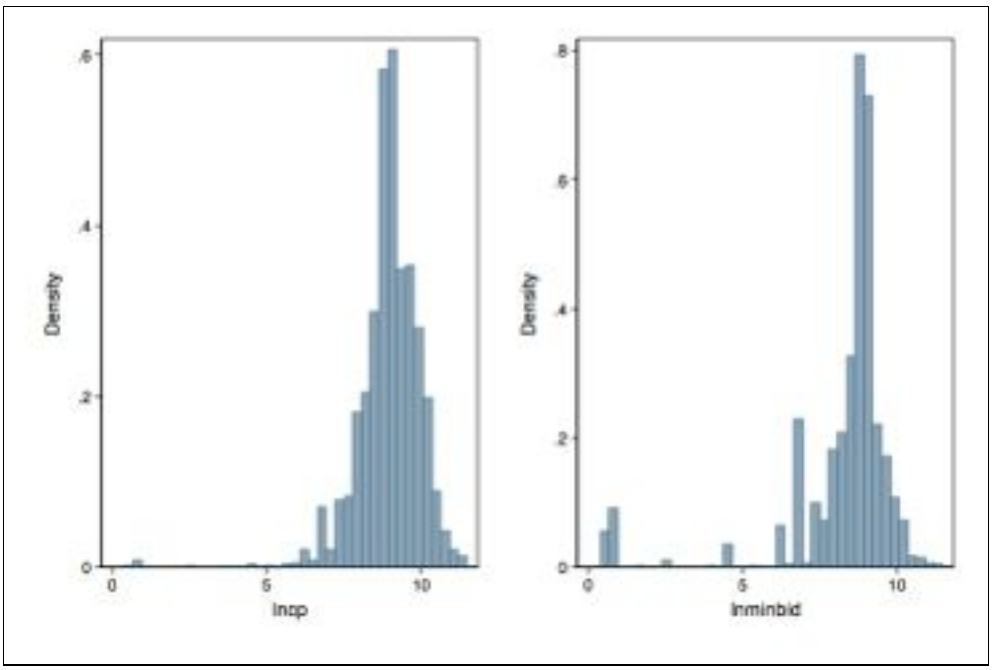


Figure 3A-3: Distribution of Sellers' Feedback

Figure 3A-4: Auctions with Buy It Now (BIN) Options

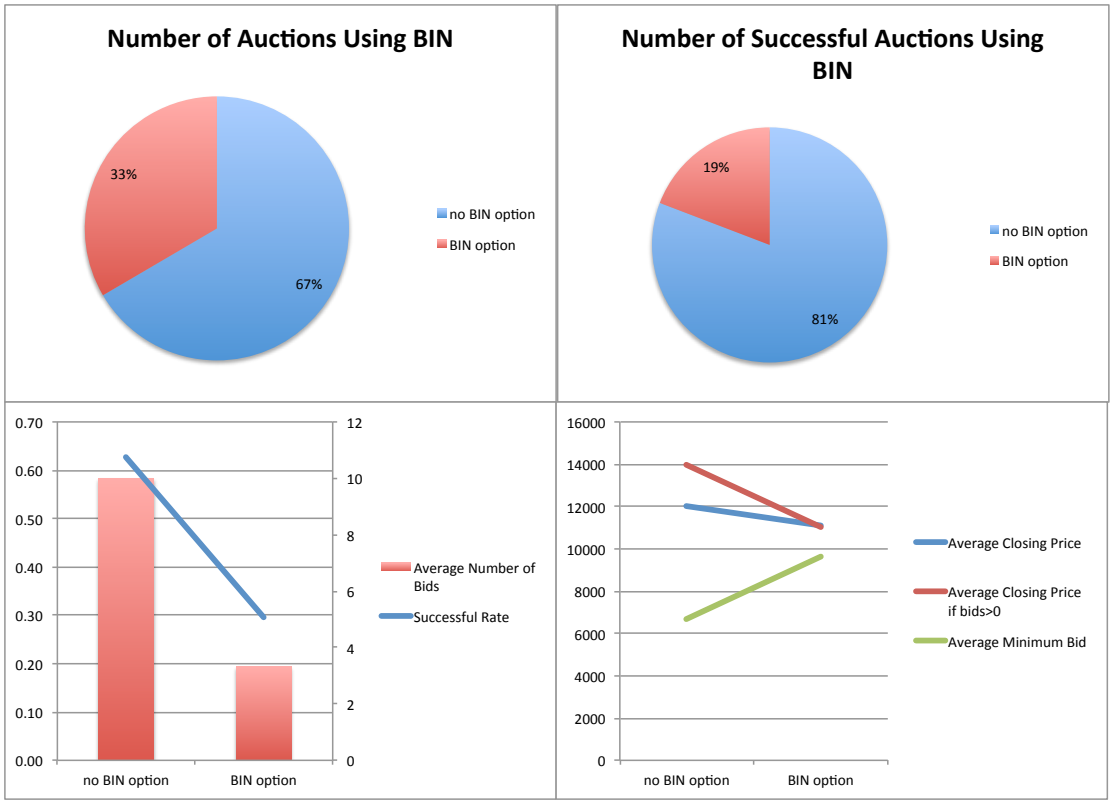


Figure 3A-5: General Features of the Concerts

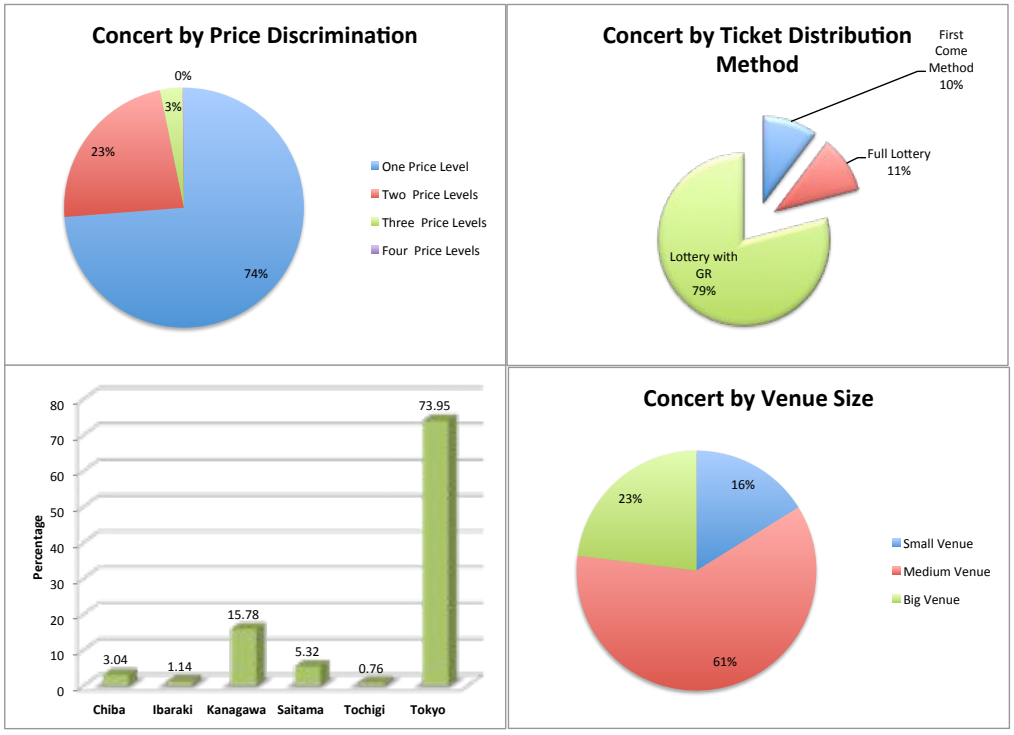


Figure 3A-6: General Features of the Concerts

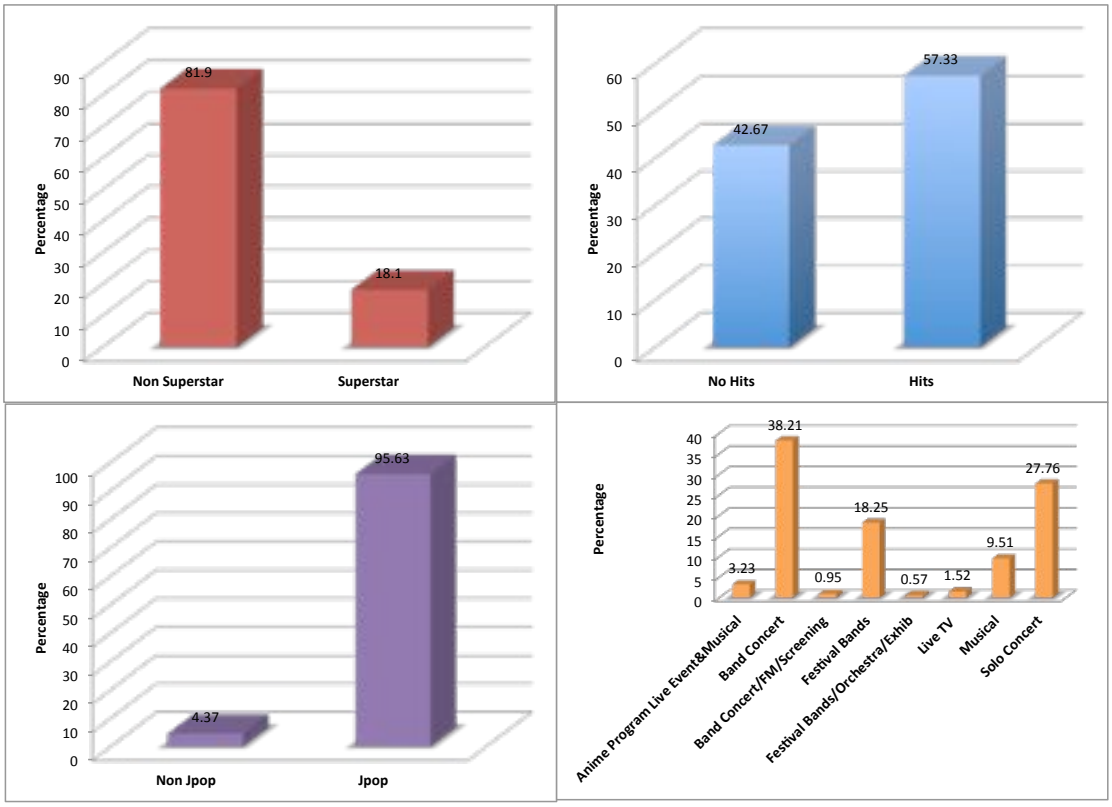


Figure 3A-7: Concert Average Days to Concert and Success

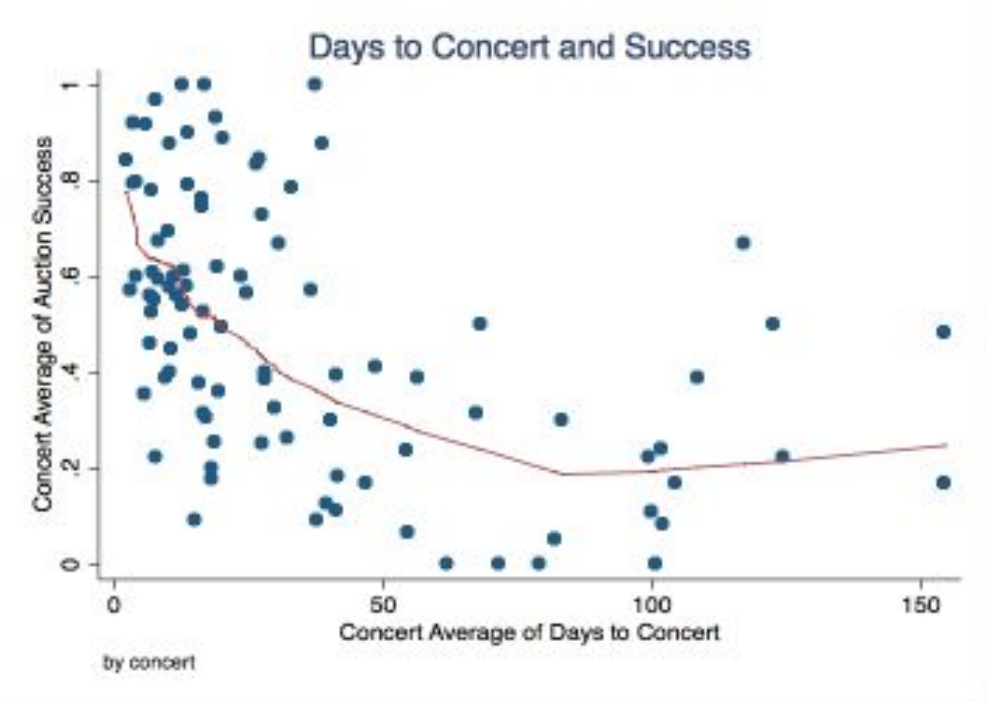


Figure 3A-8: Concert Average Days to Concert and Minimum Bid

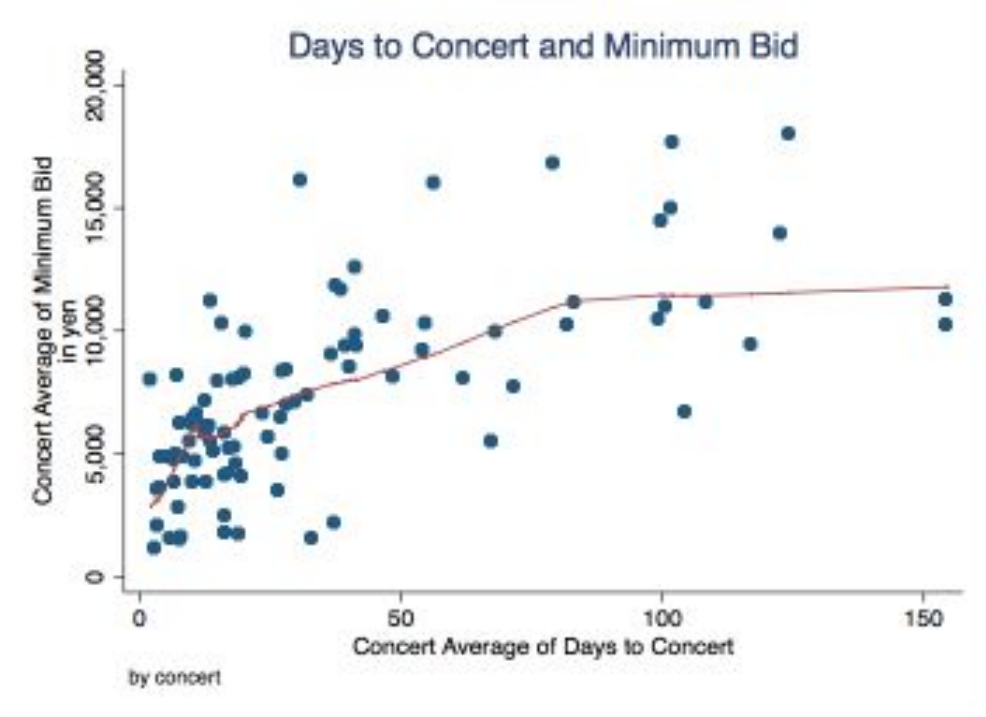


Figure 3A-9: Concert Average Days to Concert and Closing Price

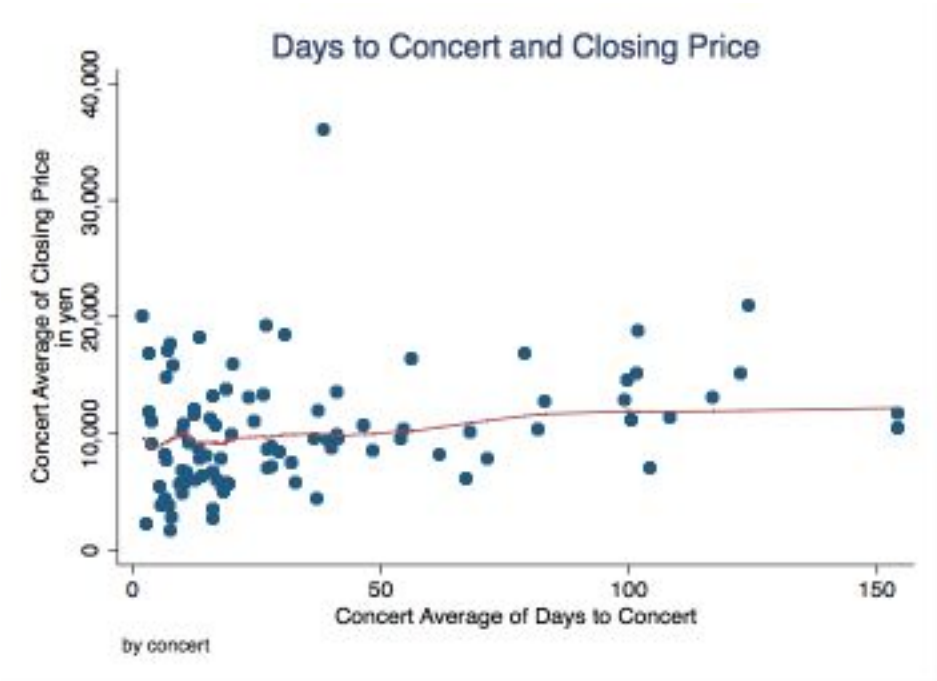


Figure 4A-1: Errormax by Seat Certainty

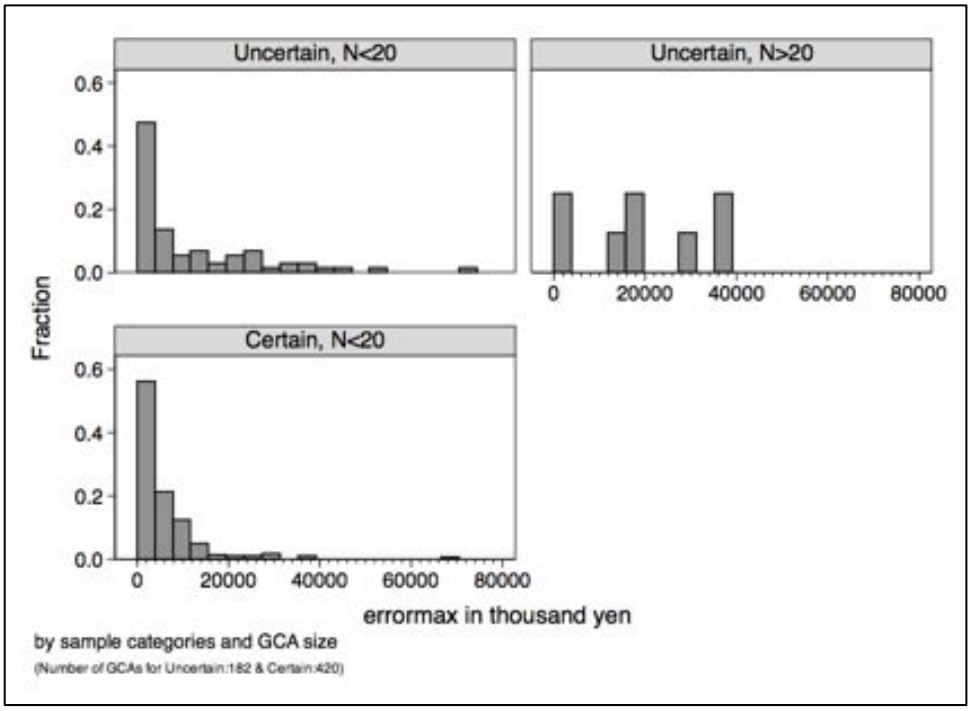


Figure 4A-2: Errormin by Seat Certainty

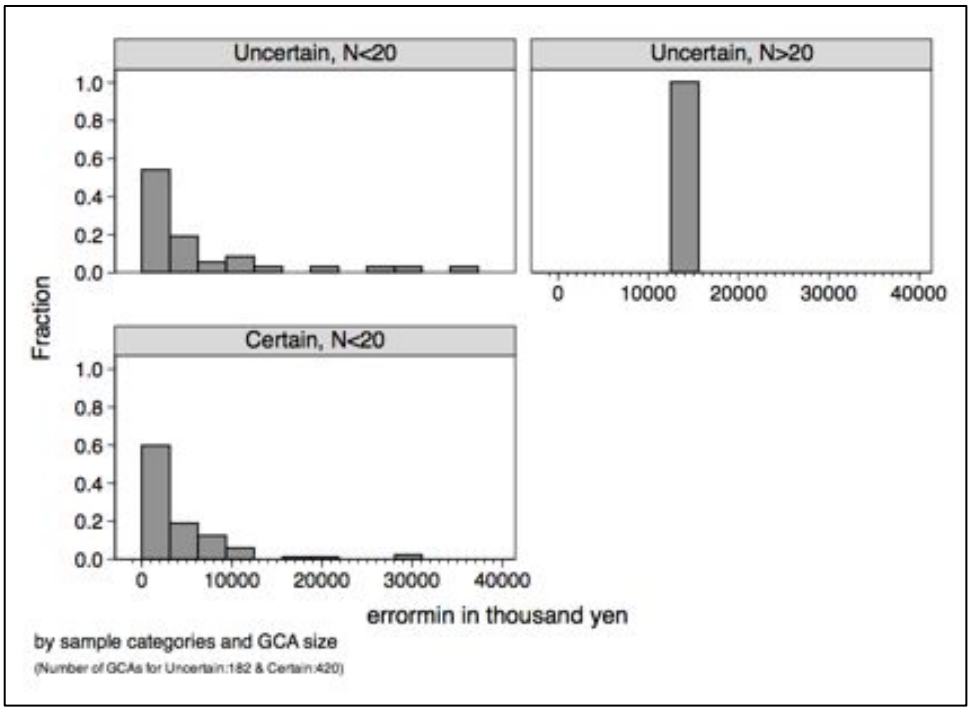


Table 4A-1: Summary Statistics of GCAs by Sample Category

	count	mean	sd	min	p25	p50	p75	max
AKB								
missedopmax	43	0.790698	0.411625	0	1	1	1	1
missedop	43	0.325581	0.474137	0	0	0	1	1
errormax	43	18195.15	16984.39	0	1000	15700	26000	70600
errormax>0	34	23011.51	15904.48	250	12500	22250	33250	70600
error	43	4078.151	8604.31	0	0	0	1250	37410
error>0	14	12525.75	11190.86	500	1250	13025	15200	37410
finemarkets	43	9.837209	7.306	2	4	9	15	31
bidmarkets	43	182.1395	248.674	1	37	98	188	1259
Uncertain								
missedopmax	182	0.45055	0.498921	0	0	0	1	1
missedop	182	0.21978	0.41524	0	0	0	0	1
errormax	182	5613.143	11608.88	0	0	0	3700	70600
errormax>0	82	12458.44	14656.38	50	1800	5725	20250	70600
error	182	1542.365	5024.734	0	0	0	0	37410
error>0	40	7017.762	8818.508	125	1100	3125	10875	37410
finemarkets	182	5.368132	5.5823	2	2	3	6	31
bidmarkets	182	61.53846	146.7751	1	1	9	65	1259
Certain								
missedopmax	420	0.585714	0.493186	0	0	1	1	1
missedop	420	0.295238	0.456694	0	0	0	1	1
errormax	420	3236.68	6350.326	0	0	600	4025	70000
errormax>0	246	5526.039	7500.937	50	1100	3025	7500	70000
error	420	1233.271	3470.324	0	0	0	540	30500
error>0	124	4177.21	5350.478	100	1150	2250	5100	30500
finemarkets	420	4.028571	2.558927	2	2	3	5	17
bidmarkets	420	23.95238	44.76145	1	2	11	31	598
Total								
missedopmax	602	0.544851	0.498399	0	0	1	1	1
missedop	602	0.272425	0.445578	0	0	0	1	1
errormax	602	3955.145	8360.297	0	0	450	4000	70600
errormax>0	328	7259.139	10217.79	50	1225	3500	8805	70600
error	602	1326.718	4002.514	0	0	0	300	37410
error>0	164	4870.027	6458.031	100	1150	2375	5875	37410
finemarkets	602	4.433555	3.785391	2	2	3	5	31
bidmarkets	602	35.31561	90.46153	1	2	10.5	34	1259

Table 4A-2: Summary Statistics of GCAs by Sample Category for Identical Sellers

	count	mean	sd	min	p25	p50	p75	max
AKB								
missedopmax	23	0.608696	0.499011	0	0	1	1	1
missedop	23	0.304348	0.470472	0	0	0	1	1
errormax	23	6437.609	10602.09	0	0	500	5750	31000
errormax>0	14	10576.07	11961.9	250	500	4432.5	23000	31000
error	23	5709.348	10758.54	0	0	0	3865	31000
error>0	7	18759.29	11781.09	500	3865	23000	26500	31000
finemarkets	23	5.304348	2.457545	2	2	6	7	9
bidmarkets	23	18.13043	24.44717	1	3	6	30	99
Uncertain								
missedopmax	50	0.38	0.490314	0	0	0	1	1
missedop	50	0.22	0.418452	0	0	0	0	1
errormax	50	3213.8	7865.636	0	0	0	500	31000
errormax>0	19	8457.368	11027.63	125	500	2000	22500	31000
error	50	2863.8	7834.254	0	0	0	0	31000
error>0	11	13017.27	12464.05	125	500	11000	25450	31000
finemarkets	50	3.62	2.302527	2	2	2	6	9
bidmarkets	50	9.78	18.7511	1	1	2	6	99
Certain								
missedopmax	87	0.517241	0.5026	0	0	1	1	1
missedop	87	0.436782	0.498863	0	0	0	1	1
errormax	87	2028.592	5117.124	0	0	100	2200	36000
errormax>0	45	3921.944	6601.916	100	500	2000	4899	36000
error	87	1864.58	5121.979	0	0	0	759.5	36000
error>0	38	4268.908	7101.874	100	500	2100	5200	36000
finemarkets	87	2.436782	1.00812	2	2	2	3	8
bidmarkets	87	7	11.73447	1	1	2	7	68
Overall								
missedopmax	137	0.467153	0.500751	0	0	0	1	1
missedop	137	0.357664	0.481072	0	0	0	1	1
errormax	137	2461.15	6259.141	0	0	0	1200	36000
errormax>0	64	5268.398	8339.532	100	500	2000	5200	36000
error	137	2229.259	6239.865	0	0	0	500	36000
error>0	49	6232.827	9211.136	100	500	2250	6500	36000
finemarkets	137	2.868613	1.696959	2	2	2	3	9
bidmarkets	137	8.014599	14.68191	1	1	2	7	99

Table 4A-3: Regression Results

	Panel Linear Regression with Fixed Effects (LPM)		Panel Logit with Conditional Fixed Effects		Probit		Panel Linear Regression with Fixed Effects		Panel Linear Regression with Fixed Effects errors>0		Panel Tobit with Mundlak		Tobit	
	missedopmax	missedop	missedopmax	missedop	missedopmax	missedop	lerrormax	lerror	lerrormax	lerror	lerrormax	lerror	lerrormax	lerror
1.good2	0.467*	0.194			0.424***	0.345*	4.255**	1.440	2.037**	2.495*	6.908***	4.204	9.411***	10.06*
	(0.186)	(0.164)			(0.0636)	(0.145)	(1.437)	(1.316)	(0.643)	(1.169)	(1.934)	(2.233)	(2.686)	(4.439)
1.bad2	0.381*	0.378**			0.250**	0.214	3.366**	3.026**	2.001***	0.782	3.490*	2.047	4.934*	5.425
	(0.159)	(0.126)			(0.0852)	(0.123)	(1.209)	(0.995)	(0.539)	(0.937)	(1.664)	(1.679)	(2.114)	(3.279)
1.medcertain2	0.437***	0.346***			0.370***	0.304***	3.544***	2.656**	1.617*	1.616	4.531***	3.151**	7.048***	9.150**
	(0.0960)	(0.1000)			(0.0611)	(0.0868)	(0.756)	(0.806)	(0.616)	(0.990)	(0.955)	(1.020)	(1.676)	(2.933)
finemarkets	0.0291***	−0.0420***	0.0318**	−0.0372	0.0389***	−0.0544***	0.231***	−0.367***	−0.00654	−0.199**	0.248***	−0.466***	0.393***	−1.567***
	(0.00574)	(0.00979)	(0.0105)	(0.0390)	(0.0103)	(0.0112)	(0.0569)	(0.0810)	(0.0268)	(0.0589)	(0.0751)	(0.0883)	(0.0816)	(0.324)
1.mbin	−0.190***	−0.100*			−0.181***	−0.117**	−1.667***	−0.865*	−0.341*	−0.561*	−1.749***	−1.002***	−2.858***	−3.556**
	(0.0502)	(0.0484)			(0.0455)	(0.0407)	(0.430)	(0.383)	(0.156)	(0.263)	(0.358)	(0.295)	(0.673)	(1.291)
bidmarkets	−0.000412	0.00157***	−0.000135	0.00133	−0.000440	0.00179***	−0.00137	0.0144***	0.00184	0.00527***	−0.00272	0.0136***	−0.00427	0.0456***
	(0.000224)	(0.000283)	(0.000774)	(0.00140)	(0.000435)	(0.000428)	(0.00253)	(0.00240)	(0.00115)	(0.00135)	(0.00297)	(0.00269)	(0.00322)	(0.00821)
mlevelr	−0.440	−0.642	−0.396	−0.294	−0.151	−0.219	−4.482	−5.776	−2.687***	0.268	−1.977	−1.644	−3.057	−5.533
	(0.400)	(0.374)	(0.381)	(0.177)	(0.322)	(0.297)	(3.155)	(3.075)	(0.582)	(0.987)	(3.287)	(2.558)	(5.168)	(8.260)
mfeed	−0.0201	−0.00451	−0.0151	0.00333	0.00262	0.0192	−0.178	−0.0255	−0.0481	0.0857	0.0537	0.152	0.0995	0.511
	(0.0206)	(0.0188)	(0.0172)	(0.0128)	(0.0184)	(0.0166)	(0.169)	(0.140)	(0.0671)	(0.142)	(0.165)	(0.131)	(0.310)	(0.469)
sdfeed	0.0387	0.0269	−0.00885	0.00190	−0.0112	−0.0144	0.349	0.215	0.130	−0.00798	−0.0318	−0.0937	−0.169	−0.354
	(0.0302)	(0.0238)	(0.0273)	(0.0127)	(0.0214)	(0.0171)	(0.248)	(0.175)	(0.122)	(0.148)	(0.233)	(0.187)	(0.355)	(0.463)
1.mpair	−0.117	−0.00564			−0.100	0.0324	−1.033	−0.0694	−0.281	0.318	−0.992*	0.353	−1.641	1.138
	(0.0639)	(0.0607)			(0.0613)	(0.0629)	(0.527)	(0.473)	(0.232)	(0.417)	(0.472)	(0.471)	(0.920)	(1.705)
period3	0.000306	−0.00138	−0.00123	−0.00140	−0.000325	−0.00106	0.00707	−0.00345	0.0273	0.0254	0.000377	−0.00350	0.00177	−0.0148
	(0.00269)	(0.00320)	(0.00209)	(0.00138)	(0.00170)	(0.00184)	(0.0213)	(0.0236)	(0.0177)	(0.0253)	(0.0205)	(0.0158)	(0.0289)	(0.0538)
mbigshop	0.158	0.000207	0.131	0.0243	0.0658	−0.00134	1.489	−0.0736	−0.183	−0.857	0.275	−0.113	0.411	−0.381
	(0.197)	(0.243)	(0.177)	(0.0989)	(0.171)	(0.146)	(1.455)	(1.987)	(0.545)	(0.506)	(1.708)	(1.372)	(2.479)	(4.168)
sdbigshop	−0.259	−0.191	−0.209	−0.111	−0.265	−0.220*	−2.009	−1.717	0.261	−0.261	−2.563	−1.721	−4.079	−5.789
	(0.234)	(0.173)	(0.223)	(0.102)	(0.198)	(0.105)	(1.807)	(1.427)	(0.524)	(0.489)	(1.827)	(1.463)	(2.732)	(2.985)
liquid	0.0443*	−0.0319	0.0414	−0.0184	0.00964	−0.00678	0.534**	−0.285	0.125	0.182*	0.139	−0.116	0.237	−0.390
	(0.0205)	(0.0217)	(0.0227)	(0.0236)	(0.0300)	(0.0268)	(0.176)	(0.186)	(0.0942)	(0.0778)	(0.277)	(0.229)	(0.438)	(0.721)
c.sdfeed#c.period3	−0.00191**	−0.00161**					−0.0142**	−0.0110**	−0.00252	0.00725				
	(0.000629)	(0.000547)					(0.00460)	(0.00379)	(0.00420)	(0.00530)				
N	601	601	506	502	601	601	601	601	328	164	601	601	601	601
N_Clust	101	101	46	44	101	101	101	101	71	64	101	101	101	101

*** *p*<0.1; ** *p*<0.05; *** *p*<0.01,panel is at artist level, the coefficients for probit and tobit regressions are marginal effects and average partial effect(APE) respectively**