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The Effect of Open Musical Contest in Korea for New-Coming Singers: Empirical Evidence from Online Music Market

신인 가수들의 오디션 프로그램이 가지는 영향: 온라인 음원 시장에서의 실증적 증거

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Abstract

The Effect of Open Musical Contest in Korea for New-Coming Singers: Empirical Evidence from Online Music Market

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Recently, broadcasting companies made audition programs for non-professional singers. They can participate in the programs without any qualifications, and through the programs, they can start their careers as professional singers. On the other hand, people who want to become singers contract with the companies and get trained. This paper examines the effect of audition programs on singers' public awareness. After I construct panel data, singers from the audition programs get higher public awareness than singers who do not. Moreover, songs that are sung by singers from audition, are more likely to be on the online music Top 100 chart with their names, which means that their songs will be listened to more than the others'.

Keywords: Musical Contest, Public awareness, Audition Program, Panel data analysis, Econometric model, Fixed effect, Linear probability model

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1 Introduction

An audition is a very useful tool to check artist's competitiveness. Especially, this method is widely known for music, art, and many fields. Through this, artists can acknowledge the public of their works, and also make income through copyright for their own creations.

Musical contests has been used to test the ability of playing musical instruments, as well as contesting the superiority of the performance of classical instruments[1] of individual players, and to recruit new team members for a team specializing in a musical ensemble. Hence, classical musical instrument players participate in such contests as a channel to introduce their performance, participate in orchestras and other bands, perform musical activities, and simultaneously release personal albums to earn revenues.

However, as music became popular, musical instruments became common and composition equipments developed, allowing not only professional musicians but also non-professional people to make their own music and album and earn money through their creation. Moreover, people can become professional singers even without special training programs provided by entertainment companies. Thus, broadcasting companies started to hold programs for potential singers so that they can have the opportunity to become musicians not only through the trainee position, but also through the programs and di-

[1] e.g., piano, violin, cello, and flute

rect contracts with companies without being an artistic trainer.

There have not been many papers dealing with the field of music in economics. Ginsburgh and Ours(2003) studies the effect of ranking in musical competition on the musicians' success. Also, Karhunen(1996) shows that the professional training artists undertake effects their employment situation. Nguyen et al(2014) shows that the merging of the online music market will work as a link between the music industry and digital revolution. Finally, Park and Lee(2017) analyzes the effect of various social media indicators on music streaming and downloads.

This paper examines the effect of audition programs on public awareness for new singers. Singers from the audition programs will get higher awareness than other singers, and people will listen to their music more than the others. For this purpose, I searched each singer's information online, and counted the number of times that singer was on the headline of online news. After constructing panel data using these information, I used this to identify the effect.

The remainder of the article is organized as follows. Section 2 describes background on the Korea music market. Section 3 introduces previous studies related to this study. Section 4 explains the data used in this study. Section 5 shows the empirical strategy used to estimate the effect of audition on the public awareness. Section 6 concludes.

2 Background

2.1 How to become a singer in Korea

In Korea, there are several ways to become a singer or a professional musician. In general, a person who wants to be a singer enters into an entertainment company. When a company receives the applicant's profile or their recorded files, it judges whether he or she has the potential to become a singer and then casts. Sometimes the company holds a closed audition. After this casting process, the company trains the member. At this stage, the member is called a trainee. A trainee is trained for a certain period; from 3 months to more than 1 year. In this time, he or she practices dancing, singing, and instruments that the company provides to make one a professional singer. The company also provides recording equipment when a singer wants to release a CD or an album. The company signs a contract that covers all costs for singer and gets a percentage of income for the album.

On the other hand, singers perform without contracting the company. They are called "independent musicians". They perform their music without the aid of the company, and pay all costs of music activities on their own account. This includes recording equipment and space for compositing songs, and instruments for playing. In general, however, since it is expensive to cover all the expense, they can also takes other jobs, or even receive investment and funds through sponsorship around them. For this reason, most of singers perform with their agency.

2.2 Audition Programs

From the early 2010's, broadcasting companies started open musical audition programs. These programs neglected application qualifications so that many potential singers could apply to the audition. The companies recorded and aired this audition process as TV programs. According to the Korea Music White Industry(2016), there are various types of audition programs, but the following two programs are categorized in a similar format, called 'discovering type'.

1. Superstar K: This was the first audition program in Korea after the format of "American Idol"; participants sing in front of the judges, and judges assess the participants and cast them into the entertainment companies. This program was broadcast from 2009 to 2016 seasonally by Mnet. This program requires applicants to perform their music by each group, and chooses 10 to 12 people over six final rounds dropping 2 people per each round and ranking them in order.

2. K-pop Star: This program is similar to Superstar K, started in 2012 and ended in 2017, broadcasted by SBS. In a similar way, judges choose 10 final applicants and rank each of them.

Through these audition programs, applicants have opportunities to make their own albums and become professional singers by contracting with the company. In addition, Each broadcasting company made programs for various types of audition using the ranking system until mid-2010. After 2017, most of these programs ended without extension. The advent of the above programs means that the selection process has been changed in that a singer could apply not only directly to the entertainment companies but also to the open audition programs in order to start a career as professional singers.

2.3 Online Music Market

This section briefly introduces the current status of online music market in Korea. According to the Korea Music White Industry (2017), Figure 1 is a survey of the actual route that the audience listen to music. This shows that more than 70% of the people use online music sites to listen to music in the recent 3 years. This concludes that most people use online sites to listen to music, though the ratio has been decreased.

Figure 2 shows how many people use online sites to listen to music rather than physical music(or physical recordings)[2]. According to this chart, 77% of people have experience using online sites, rather 23% of people use physical music.

[2]Physical music means stored music in CD, DVD, blueray, cassette tape and LP.

Figure 1: Share of music listening

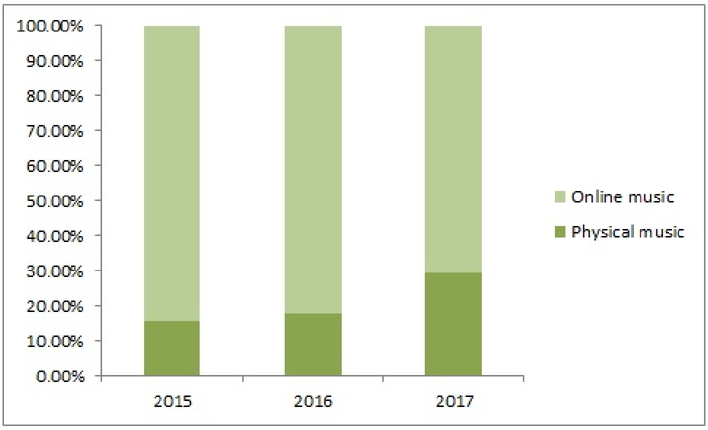


Figure 2: Experience in listening to music through online sites

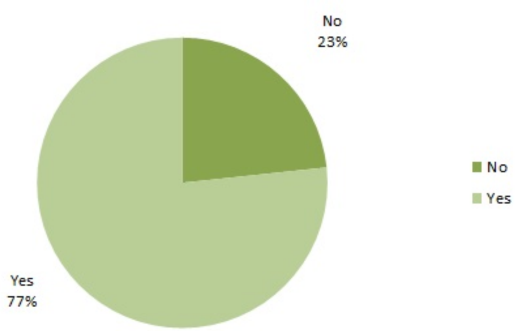


Figure 3: Preference on online music sites

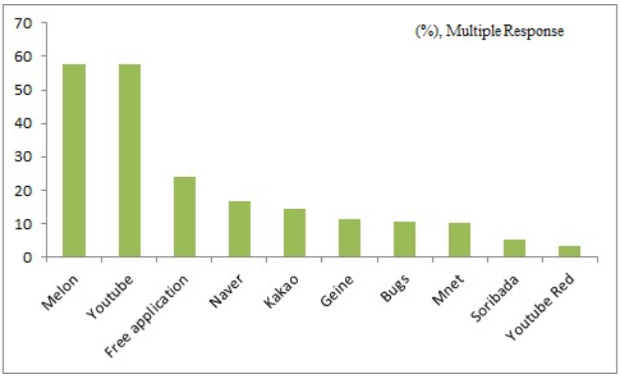


Figure 3 shows that Melon is the most frequently used of all sites. About 58% of people use Melon to listen to music, and 57% of people use Youtube. Melon provides various kinds of albums and music videos on the site that makes people easy to access. Youtube also provides various music contents. According to the graph, those two sites are mainly used to listen to music on the site, and they also provide mobile applications. But they do not allow people to play music free. Music streaming requires the certain amount of fee, and Youtube requires to see some advertisements when people listen to music.

3 Literature Review

There are a few papers that analyze music, or music markets in economics. Especially, papers that analyze musical contest have been rarely published.

Ginsburgh and Ours(2003) analyzes how the music contest affects the success of the musician. Authors tried to collect 132 musicians who took part in the Queen Elizabeth Musical Competition and investigated data to measure success. The paper mentions that the success of musicians can be measured by collecting sales data of LP and CD, and critique from music critics. However, since collecting these sales data is unavailable, the paper used the number of their LPs and CDs that are kept in the Belgian public listening library, record data from the French catalogue Diapason, and rankings from Belgian music critics. Using these data, the authors identified two facts: ranking is affected by the order of appearance in the contest and the time, and also affects the indicator of success.

P.Karhunen(1996) deals with the issue of professional training for artists. The paper discusses the effect of formal training on artists' employment situation in Finland. Using surveys of theatre and dance artists, the author insists that the formal training works as a signal of an initial proof of artistic talent. Although the effect of training on artists' earning is ambiguous, the study mentions that it affects the labor market in many ways. Especially, by training, it is possible to regulate the number of entrants in the art field, and increases the advantage of the occupation.

G.D.Nguyen, S.Dejean and F.Moreau(2014) shows the advantage of online music market. The paper examines that streaming does not negatively impact on music sales, but positively impact the attendance of musicians' performances. Streaming simply works as a channel to notify recorded music, so it does not negatively affect the music industry. Instead, it can be a link between the music industry and digital revolution.

Park and Lee(2017) examines the effect of social media indicators on streaming and downloading music. Authors collected these indicators from online music sites and Youtube using data mining, and identified that these indicators affect the consumption of music.

4 Data

In this section, I present how I collected and constructed the data. Since the audition programs were popular in the early and mid 2010's, I focused on 190 singers who debuted from 2013 to 2016 and currently under contract with the entertainment companies. As Ginsburgh and Ours(2003) showed, the best way to measure an individual singer's success is to collect album sales data. On the other hand, online music sales depends on music downloads and streaming by audiences. Hence, the sales data can be used as a measure of public awareness. The more the albums or music are sold, the higher public awareness achieved.

The Recording Industry Association of Korea provides the album sales data, but it is only available up to 2007. In other words, the data related to rising singers in the 2010's is hard to collect. Thus, I collected the number of online news headlines as a proxy of public awareness. The high public awareness of a singer implies that the press has a high proportion in dealing with the singer. Using the Internet news search engine, I collected the number of news articles that mention the name of a singer in the headline by year. For the search engine, I used the site "Naver". Also, since some statistical programs provide a news collecting package, I have tried out the program, but the result of collected data were not that different.

Our main purpose of this study is to identify the effect of the audition programs for each singer on their public awareness. Ginsburgh and Ours(2003) collected each musician's ranking from the musical contest. But in this study, I coded whether a singer participated in an audition in a particular year as a dummy variable. I also searched the basic information of the singers such as age, gender, and whether a singer performs as a group and he or she comes from other countries.

Moreover, singers perform by making songs and releasing albums. They do not merely sing and perform only on TV. Hence, I collected the number of singers' albums released in a certain year, and classified the types of album as single[3], EP[4], Normal[5], and OST[6]. Most of music sites in Korea classify OST as an independent album. Also, the variable 'Featuring' is coded as 1 whether singers received help from other famous singers in the year they performed. I collected these album data through Melon, one of the largest online music providing site in Korea. The number of comments on singers' albums in Melon site are also collected as a measure of audiences' activities. They leave comments on each singer's album and if singers or their songs are well-known, audiences write reply on the comment page.

If a song is played often, it means that streaming frequency increases, which has a direct correlation to income in Korea. Most of online music streaming sites provide a one-minute free streaming ser-

[3]An album that consists of 1 song.

[4]An album that consists of 3 to 5 songs

[5]An album that consists of more than 5 songs

[6]OST means "Original Sound Track". It means the music used in movie, advertisements, and drama

vice per a song. If people want to listen the whole song, providers require people to pay a certain fee to listen. Hence, I also investigated top-ranked singers and their songs for each year in the Top 100 chart provided by the Korea Music Content Association[7]. However, since there are numerous singers' songs on the chart, locating the singers of our focus is relatively difficult on the yearly Top 100 chart. Instead, I used the monthly Top 100 chart on streaming, and coded it as a dummy variable if a singer's song and name was on the chart. A singer's song on the Top 100 chart means that the song is widely listened to and audiences know the song and the artist.

Considering all these information related to a singer in a certain year, I constructed unbalanced panel data. One limitation is that since the data is depending on data-collecting process, there are some missing values. Therefore, the closed information about singers were not be able to be found. The following table describes the dataset.

[7]The association provides yearly, monthly, and weekly Top 100 chart on music streaming and downloads.

Table 1: Summary Statistics

	N	Mean	Std. Dev	Min	Max
News	698	0.1168	0.3214	0	41059
Top100	702	0.1168	0.3214	0	1
Audition	702	0.1595	0.3662	0	1
Comment	657	3756.473	21978.55	0	296050
Group	702	0.5171	0.5001	0	1
Female	702	0.4772	0.4998	0	1
Age	649	23.8473	4.3431	14	38
Foreign	702	0.0456	0.2087	0	1
Single Album	672	0.8274	1.2919	0	13
EP Album	672	0.3125	0.6324	0	4
OST Album	672	0.2426	0.6922	0	8
Normal Album	672	0.0893	0.3151	0	2

5 Econometric Models and Result

5.1 The Effect of Audition Programs on Public Awareness

5.1.1 Panel Data Analysis

In this section, I set the following hypotheses for the research.

1) The audition programs in a certain year will get high public awareness of singers, rather than training programs provided by entertainment companies.

2) Participating in the audition programs will affect both this year's public awareness and next several years' public awareness.

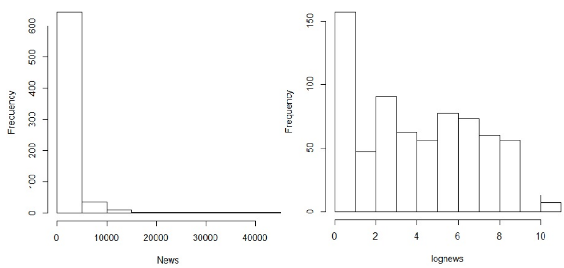
The first hypothesis claims that the effect of participating in the audition programs on each singer's public awareness exists. To identify the effect of audition programs, I constructed the following equation:

$$\log(1 + Y_{it}) = \delta A_{it} + \beta' X_{it} + \alpha_i + \epsilon_{it}. \tag{1}$$

In equation (1), Y_{it} is a dependent variable that means public awareness. A_{it} means whether singer i takes part in an audition on time t. X_{it} is a vector of control variables for each singer. α_i is an unobservable time-invariant individual effect. This α_i, for example, individual musical ability, propensity and maturity, may not be observed, but it effects the individual musical characteristics in that it may decide whether to participate in the program or not. Hence, this factor must be considered in our estimation.

We focus on Y_{it}. It is measured as the number of online news headlines that the singer's name is directly mentioned. This can differ among singers; a well-known singer gets high public awareness, which leads to a high number of Y_{it}. On the other hand, a not well-known singer has low public awareness, which leads to a zero number of Y_{it}. Hence, 0 in Y_{it} may distort the regression result. Moreover, extremely high number in Y_{it} may also affect the result. In Table 2, we may see that the number of news is distributed from 0 to 41059. In order to prevent this, I use $\log(1 + Y_{it})$ instead of Y_{it}. Figure 4 is histogram of the number of news before and after log-transformed.

Figure 4: Histograms of $News$ and $\log(1 + News)$



Throughout the estimation process, missing values are dropped. Using the fixed effect model, the unobservable individual effect α_i is eliminated. The result is on Table 2; public awareness is coded as the number of online news headlines that each singer's name is directly mentioned.

Table 2: The effect of audition programs: Fixed effect model

	$\log(1+News)_{it}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Audition_{it}$	3.539***	3.525***	3.517***	3.497***	3.341***	3.472***	3.472***
	(0.193)	(0.188)	(0.192)	(0.192)	(0.264)	(0.247)	(0.248)
$Female_{it}$		2.023		2.377***	2.275**	1.951***	1.456
		(1.424)		(0.704)	(0.696)	(0.528)	(0.869)
$Group_{it}$			-1.572	-1.796*	-2.292**	-1.925**	-2.347**
			(1.041)	(0.734)	(0.781)	(0.583)	(0.744)
Age_{it}					-0.0939	-0.0926	-0.0906
					(0.0966)	(0.0889)	(0.0890)
$Foreign_{it}$					-0.246	0.0813	0.0865
					(0.314)	(0.192)	(0.193)
$Featuring_{it}$						0.545*	0.536*
						(0.236)	(0.233)
$Single_{it}$						0.262***	0.264***
						(0.0513)	(0.0515)
EP_{it}						0.448***	0.446**
						(0.134)	(0.134)
OST_{it}						0.324**	0.314*
						(0.124)	(0.125)
$Normal_{it}$						0.539**	0.534**
						(0.199)	(0.199)
$(Female \times Group)_{it}$							1.001
							(1.272)
Constant	3.444***	2.484***	4.263***	3.252***	5.833*	5.122*	5.283*
	(0.0310)	(0.683)	(0.533)	(0.352)	(2.604)	(2.372)	(2.362)
N	698	698	698	698	645	615	615

Robust standard errors are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 2 shows the effect of audition programs on the online news. In regression (1), the effect of participating in the audition programs leads singers to receive about 33.47 more articles that mention the singers who take part in the program in a certain year more than those who do not. This can be interpreted that singers from audition get public awareness measured in $\log(1 + News)$ more than the other singers. Regression (2) adds the gender effect whether female singers achieve higher public awareness than male singers. Regression (3) adds the group effect whether singers perform as group. Regression (4) considers both gender and group effect. Regression (5) considers singers' age and origins. Regression (6) adds the types of singers' album. Regression (7) additively controls the effect of female group singers. Regression (4) to (6) show that female singers take more news articles rather than male singers. Also, non-group performing is more likely to be written on news than group performing. These results show that after controlling other factors, the effect of audition programs allow singers to achieve higher public awareness in a certain year.

The second method is using the Mundlak approach. Mundlak(1978) suggests the idea of controlling the unobservable individual fixed effect using individual characteristics. Using these control variables, individual fixed effect is separated in the relevant part of individual charcteristics and irrelevant part. Then, the irrelevant part of the unobservable effect still causes endogeneity but it is alleviated. Using the random effect model, the result of the regression using the Mundlak approach is on Table 3.

The regression order is similar as Table 3. In regression (1), singers

Table 3: The effect of audition programs: the Mundlak approach

	$log(1+News)_{it}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Audition_{it}$	3.458***	3.448***	3.453***	3.443***	3.369***	3.404***	3.407***
	(0.169)	(0.168)	(0.169)	(0.168)	(0.188)	(0.181)	(0.182)
$Female_{it}$		0.783**		0.793**	0.799**	0.858**	1.065**
		(0.289)		(0.292)	(0.295)	(0.276)	(0.372)
$Group_{it}$			-0.148	-0.161	-0.203	-0.248	-0.0397
			(0.271)	(0.270)	(0.275)	(0.259)	(0.356)
Age_{it}					-0.0417	-0.0713	-0.0714
					(0.0516)	(0.0501)	(0.0501)
$Foreign_{it}$					0.261	0.758	0.732
					(0.565)	(0.548)	(0.548)
$Single_{it}$						0.295***	0.294***
						(0.0602)	(0.0603)
EP_{it}						0.460***	0.462***
						(0.135)	(0.135)
OST_{it}						0.421***	0.426***
						(0.114)	(0.115)
$Normal_{it}$						0.557*	0.560*
						(0.227)	(0.227)
$(Female \times Group)_{it}$							-0.430
							(0.518)
Constant	4.138***	2.951**	4.213***	3.018**	3.000**	2.666**	2.645**
	(0.894)	(0.991)	(0.913)	(1.012)	(1.034)	(0.966)	(0.964)
N	637	637	637	637	635	615	615

Robust standard errors are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

from auditions receive higher public awareness by 3.44 compared to those from other channels, which means that the audition programs allows singers to receive approximately 30.19 more articles. Regression (2) to (7) follows the same procedure from the previous regression, and we do not lose the robustness of the regression result of $Audition_{it}$ on dependent variable. Also, regression (4) to (7) shows that the effect of gender difference is statistically significant: female singers receive more articles than male singers. In regression (6) and (7), the number of singers' released albums also significantly affect to increase the public awareness.

Now we investigate the effect of audition in the previous years on the coming year's public awareness. When a singer takes participate in the audition programs in a certain year, their public awareness will be increased not only in this year, but also in the following years. In Korea, when journalists write news, they often mention the singer's name and the fact that singers participated in the audition programs. Hence, to identify the effect, I considered the following equation:

$$\log(1 + Y_{it}) = \sum_{k=0}^{3} \delta_k A_{it-k} + \beta' X_{it} + \alpha_i + \epsilon_{it}. \tag{2}$$

Using the fixed effect model, the estimation result is reported in Table 4. Singers participating in audition in time t does not changes among regression (1) to (4). Regression (2) adds one lagged variable and this comes out statistically significant, and the result of the independent variable $Audition_{it}$ is also significant. Singers' public awareness in a certain year is affected by taking the audition programs not only in the same year, but also in the last year. They receives about 2.36 more articles if they participates in the last year's audition, and receives about 48.4 more articles from the current year's audition. Regression (3) adds two-period lagged variables on regression (2), and regression (4) is with all lagged variables. Both regression results imply that more than 2 years lag of audition's effect is not that significant. In conclusion, singers who participate in an audition in time t has positive effect on the public awareness in that time, and if they come from last year's audition, it is still effective in the current year.

5.1.2 Propensity Score Matching

Another method to identify the effect of audition programs is using propensity score matching. This method is used to identify the effect of audition programs on public awareness controlling the individual heterogeneity that affects whether singers attend on the audition programs. The average treatment effect is calculated from the difference between singers who participated in the audition and the control group's similar propensity score. Using the several control variables that decide whether to attend on the audition programs, each singer's propensity score is derived. After matching singers from treatment group and control group by similar propensity scores, the average

Table 4: The effect of audition programs: Distributed lag model

	$\log(1+News)_{it}$			
	(1)	(2)	(3)	(4)
$Audition_{it}$	3.473***	3.900***	4.046***	3.759**
	(0.247)	(0.982)	(1.188)	(1.242)
$Audition_{it-1}$		1.211***	1.410***	1.660***
		(0.215)	(0.309)	(0.295)
$Audition_{it-2}$			0.254	-0.0201
			(0.198)	(0.212)
$Audition_{it-3}$				0.243
				(0.301)
$Female_{it}$	1.950***	1.455*	0.648	0.399
	(0.528)	(0.623)	(0.591)	(0.356)
$Group_{it}$	-1.926**	-0.967	-0.210	1.541
	(0.582)	(0.646)	(0.714)	(0.994)
Age_{it}	-0.0930	0.0283	0.0942	0.368*
	(0.0883)	(0.0923)	(0.114)	(0.142)
$Featuring_{it}$	0.545*	0.662*	0.720*	1.840**
	(0.235)	(0.254)	(0.297)	(0.654)
$Single_{it}$	0.262***	0.200**	0.134	-0.173
	(0.0513)	(0.0741)	(0.0864)	(0.105)
EP_{it}	0.448***	0.635***	0.417	-0.331
	(0.134)	(0.164)	(0.236)	(0.442)
OST_{it}	0.324**	0.324***	0.373***	0.453***
	(0.123)	(0.0911)	(0.103)	(0.110)
$Normal_{it}$	0.540**	0.222	0.0600	-0.685
	(0.199)	(0.122)	(0.161)	(0.371)
Constant	5.135*	1.573	-0.168	-8.202
	(2.353)	(2.501)	(3.211)	(4.168)
N	615	444	278	153

Robust standard errors are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

treatment effect is derived from the difference between the singers from each group.

There are several matching methods: Stratified matching, nearest-neighbor matching, radius matching, kernel matching. Stratified matching is dividing the entire propensity score into several groups and each group of audition and non-audition singers are matched. Nearest-neighbor matching is one-to-one matching with similar score within each group. Radius matching is a method of matching singers within a predetermined range. Finally, kernel matching is using the difference of each group's score to calculate weight and matches.

To derive propensity score, I used probit model to calculate the probability that singers took audition programs and derived propensity score using the observable control variables, then used the matching strategies mentioned above. The result of the matching is on Table 5.

Table 5: Average treatment effect using propensity score matching

	Number				
Matching	Treatment	Control	ATT	Std.Error	t-value
Stratification	109	444	3.357***	0.226	14.838
Nearest-Neighbor	109	127	3.764***	0.326	12.370
Radius	15	441	3.697***	0.511	3.262
Kernel	109	444	3.372***	0.217	16.237

Though the average treatment effect varies depending on the matching method, singers from the audition programs receive higher public awareness rather than those from other channel. Each matching strategy shows that by taking the audition programs, singers are able to get more news articles. For example, using stratified matching, the average effect of the audition programs attendance for singers will lead to 3.357 higher value of $log(1 + News)$, about 27.7 more articles than not attending the program. This is not that different from the previous results.

Therefore, we can derive the following conclusion. Singers who debuted from the audition programs achieve higher public awareness in a certain year than those who do not. Moreover, the public awareness in a year is affected by the last year's audition participation.

5.2 Singers on Top 100 chart

In this section, we investigate whether singers who participated in an audition are more likely to be top-ranked. As we discussed in section 4, a song will be recognized by the audiences with the singer's name. Then people will recognize the singer by the song. If the song is played in many times, the singer will make profit through the songs and become popular. Hence, if a singer is on top ranking, we can imply that a singer became famous.

Since the number of music streaming and downloads are limited, I used the Top 100 ranking as a proxy of popularity, as the ranking variable can indicate whether a singer's song and name is listed at least once on the monthly Top 100 chart. To analyze this, I consider the following model:

$$Y_{it} = \delta A_{it} + \beta' X_{it} + \alpha_i + \epsilon_{it} \tag{3}$$

Y_{it} means whether a singer's name is on the chart. The other variables are the same as we have analyzed in the previous section. Hence, this model is examining the probability whether singers from the audition programs, will be listed on the chart compared to those from other routes.

I reported the estimation result on Table 7 using linear probability model with fixed effect. In regression (1) the probability that a singer's song and singer's name is on the chart is 6% more than singers from the other channel. Regression (2) to regression (6) are adding control variables that we have done in the previous section. However, the number of comments is added on the regression as a control variable. Audiences leave comments on the sites while they listen to singers' song and music. Hence, if there are lots of comments on the songs, it means that these songs are likely to be on the chart. Hence, the number of comments is used to control the audiences' activities on each singer. To prevent the distortion of regression result, the variable is log-transformed, following the similar way on news variable. The result of regressions show that after the effect of audiences' ac-

Table 6: Estimated probability of being on the chart for singers: Linear probability model

	$Top100_{it}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Audition_{it}$	0.0600*	0.0894**	0.0888**	0.0901**	0.0860**	0.0865**	0.106**
	(0.0318)	(0.0327)	(0.0325)	(0.0326)	(0.0333)	(0.0331)	(0.0471)
$\log(1 + Comment)_{it}$		0.0250**	0.0250**	0.0255**	0.0241**	0.0154	0.0157
		(0.00825)	(0.00824)	(0.00838)	(0.00864)	(0.00932)	(0.0103)
$Female_{it}$			0.0895*	0.0797	0.0630	0.0516	0.0633
			(0.0540)	(0.0808)	(0.0813)	(0.0813)	(0.0870)
$Group_{it}$				0.0497	0.0543	0.0326	0.0235
				(0.0636)	(0.0758)	(0.0776)	(0.0860)
Age_{it}					-0.00695	-0.00604	-0.00475
					(0.00736)	(0.00704)	(0.00754)
$Featuring_{it}$					0.0462	0.0359	0.0241
					(0.0431)	(0.0419)	(0.0389)
$Single_{it}$						0.0198*	0.0199*
						(0.0114)	(0.0114)
EP_{it}						0.0282	0.0307
						(0.0235)	(0.0240)
OST_{it}						0.00541	0.00869
						(0.0213)	(0.0211)
$Normal_{it}$						0.0549	0.0579
						(0.0494)	(0.0500)
$log(1 + News)_{it}$							-0.00449
							(0.00775)
Constant	0.107***	-0.00424	-0.0473	-0.0703	0.104	0.105	0.0851
	(0.00507)	(0.0328)	(0.0429)	(0.0565)	(0.211)	(0.204)	(0.222)
N	702	657	657	657	602	601	597

Robust standard errors are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

tivities are controlled, still the audition programs effect is significant. Regression (7) considered the number of online news that represents public awareness. A singer's name on the chart is depending on not only a singer's profile , but also on public awareness so that people can listen to the singer's music. However, our main interesting variable $Audition_{it}$ does not lose the significance, which means that if a singer comes from an audition, his or her name is likely to be listed on the top ranking chart in a certain year.

Table 7 is the estimation result using the Mundlak approach. I found that the effect of audition programs for singers does not change from regression (1) to regression (7) compared to the previous fixed effect model on Table 6. According to Table 7, the probability that singers from the audition programs will be on the chart is estimated from 6% to 10%, similar to the previous estimation.

We also consider the previous year's audition effect in our model. As we've analyzed the effect of audition programs in the previous years on the public awareness before, we follow the same procedure. I constructed the following equation to examine the effect of audition programs not only in a certain year, but also the last several years:

$$Y_{it} = \sum_{k=0}^{2} \delta A_{it-k} + \beta' X_{it} + \alpha_i + \epsilon_{it} \qquad (4)$$

Using the fixed effect model, the result is on Table 8. In Table 8, the effect of audition programs in time t has a positive effect of being

Table 7: Estimated probability of being on the chart for singers: the Mundlak approach

	$Top100_{it}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Audition_{it}$	0.0609**	0.0848***	0.0842***	0.0858***	0.0809**	0.0810**	0.100**
	(0.0238)	(0.0233)	(0.0233)	(0.0233)	(0.0261)	(0.0262)	(0.0349)
$\log(1 + Comment)_{it}$		0.0257***	0.0257***	0.0264***	0.0240***	0.0152**	0.0156**
		(0.00536)	(0.00536)	(0.00542)	(0.00583)	(0.00690)	(0.00702)
$Female_{it}$			0.0901	0.0784	0.0646	0.0524	0.0642
			(0.0954)	(0.0963)	(0.0974)	(0.0987)	(0.0976)
$Group_{it}$				0.0595	0.0538	0.0308	0.0216
				(0.0670)	(0.0706)	(0.0721)	(0.0746)
Age_{it}					-0.00658	-0.00575	-0.00476
					(0.00742)	(0.00747)	(0.00750)
$Featuring_{it}$					0.0447	0.0338	0.0224
					(0.0308)	(0.0314)	(0.0311)
$Single_{it}$						0.0203**	0.0205**
						(0.00973)	(0.00962)
EP_{it}						0.0272	0.0298
						(0.0205)	(0.0201)
OST_{it}						0.00507	0.00844
						(0.0172)	(0.0169)
$Normal_{it}$						0.0586*	0.0615*
						(0.0339)	(0.0332)
$\log(1 + News)it$							-0.00485
							(0.00715)
Constant	-0.241**	-0.245**	-0.244**	-0.245**	-0.229*	-0.228*	-0.232**
	(0.119)	(0.123)	(0.123)	(0.123)	(0.120)	(0.117)	(0.118)
N	631	605	605	605	601	601	597

Robust standard errors are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

on the top 100 chart in the same year, though it is not significant in regression (2) to (4). However, in regression (2) and (4), the one-period lagged audition variable is estimated negatively. Participating in the audition in the last year causes 5.89% and 8.66% lower being on the chart. We can guess the reason considering the following fact; Since thousands of songs are released on the market, singers' name and their songs are rapidly changed while singers from entertainment training programs have more opportunity to be on the air to inform their songs and performances to audiences for relatively long periods, which leads to have more chance being on the chart. Hence, the probability of being on the chart in this year, will be decreased if singers took auditions in the past.

Table 8: Estimated probability of being on the chart: Distributed lag model

	$Top100_{it}$			
	(1)	(2)	(3)	(4)
$Audition_{it}$	0.106*	0.0370	0.0503	0.0427
	(0.0471)	(0.0937)	(0.106)	(0.0943)
$Audition_{it-1}$		-0.0589*	-0.102	-0.0866*
		(0.0322)	(0.0651)	(0.0517)
$Audition_{it-2}$			-0.0241	-0.0175
			(0.0370)	(0.0354)
$\log(1 + Comment)_{it}$	0.0157	0.0135	0.00942	0.0104
	(0.0103)	(0.0116)	(0.0132)	(0.0131)
$Female_{it}$	0.0633	0.0755	-0.0470	-0.0444
	(0.0870)	(0.0532)	(0.0391)	(0.0372)
$Group_{it}$	0.0235	-0.0363	0.00339	0.0000488
	(0.0860)	(0.0557)	(0.0480)	(0.0483)
Age_{it}	-0.00475	-0.00940	-0.0131	-0.0127
	(0.00754)	(0.00943)	(0.0111)	(0.0108)
$Featuring_{it}$	0.0241	0.0534	0.0284	0.0260
	(0.0389)	(0.0392)	(0.0392)	(0.0399)
$Single_{it}$	0.0199*	0.0132	0.00626	0.00651
	(0.0114)	(0.0107)	(0.00947)	(0.00979)
EP_{it}	0.0307	-0.00904	-0.0652	-0.0662
	(0.0240)	(0.0277)	(0.0525)	(0.0527)
OST_{it}	0.00869	-0.0160	-0.00867	-0.00710
	(0.0211)	(0.0243)	(0.0301)	(0.0306)
$Normal_{it}$	0.0579	0.0512	0.0215	0.0202
	(0.0500)	(0.0474)	(0.0325)	(0.0320)
$\log(1 + News)_{it}$	-0.00449	0.00750	0.00944	0.00966
	(0.00775)	(0.00902)	(0.0113)	(0.0113)
$\log(1 + News)_{it-1}$				-0.00443
				(0.0112)
Constant	0.0851	0.224	0.405	0.403
	(0.222)	(0.263)	(0.309)	(0.301)
N	597	433	270	269

Robust standard errors are reported in parentheses

* $p < 0.1$, * $p < 0.05$, * $p < 0.001$

6 Conclusion

In this paper, I introduced audition programs held by broadcasting companies. These auditions give singers higher awareness if they applied through the programs. Without the help of professional training programs provided by the entertainment companies, singers are able to contract with the companies as professional positions. Also, with the advancement of the online music market, these singers compose their own songs, and release them in the market so that the audience can listen to the music by streaming or downloading, leading to income for singers.

Our main purpose of this study is to examine the effect of audition programs on new singers on the public awareness. Previous studies related to economic analysis on music market rarely exist, and one of these studies shows that the music sales data is hard to be collected. Considering the limitation of data, I tried to gather the number of news articles that mention the name of a singer using the Internet search engine. Also, by collecting the information of a singer, I constructed the panel data for this study. Using the number of news articles as a proxy of public awareness, I found that audition programs in a certain year may affect public awareness not only in the same year, but also in the last year. Moreover, the name of a singer who participated in the audition is likely to be listed on the same year's Top 100 chart, a list that audiences mainly listen the music and see the name. However, if singers participate in the audition programs in the last year, they have lower chance to being on this year's chart.

This study has the following implication. Since the entertainment companies mainly trains the singers that are suitable for their profitability, the audition programs allow potential singers another channel to become professional singers. Hence, the companies can cast potential singers without spending much on the training system. Also, the companies should consider not only producing their profitable singers such as K-pop idols, but also finding musically competitive singers regularly. For broadcasting companies, since the audition programs roll a new channel of being professional singers for general people, it should be continued regularly.

However, this study also has some limitations. First, this study does not consider independent musicians. There are limited information about these artists, so it is impossible to collect all of the independent musicians' information. Also, since the data is depending on searching and collecting, some missing information can not be treated effectively.

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국문초록

근래에 들어, 비전문 가수들을 대상으로 하는 방송사 주관 오디션 프로그램이 방영되면서, 참가자들은 어떠한 자격조건 없이 자유롭게 오디션 프로그램에 참여할 수 있게 되었다. 그리고, 오디션에 참여함으로서 연예 기획사와 계약을 맺음으로 인해 가수로서의 경력을 시작할 수 있게 되었다. 반면에, 다른 경로를 거치는 사람들은 기획사가 제공하는 연습 프로그램을 거쳐서 전문 가수활동을 하게 되었다. 본 연구의 목적은 이러한 오디션 프로그램을 거쳐 데뷔한 가수들이 대중 인지도를 더 많이 받는지를 알아본다. 고정효과 모형을 비롯한 패널 모형 분석 방법을 통해, 오디션 출신 가수들이 대중 인지도를 더 많이 받는다는 것을 발견했다. 게다가, 이 가수들이 작곡하여 들려지는 음악이 다른 경로를 거친 가수들의 음악보다 음원 사이트의 Top100 차트에 더 많이 올라갈 가능성이 있다는 사실도 발견했다.

주요어: 음악 경연, 대중 인지도, 오디션 프로그램, 패널 분석, 계량모형, 고정효과, 선형확률모형

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