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ANALYZING BOX OFFICE REVENUES OF UNITED STATES BY USING LONG RUN REGRESSION EQUATIONS

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Abstract

This study analyzes the determinants of box office revenues by using four different cointegration regression models (Fully Modified Ordinary Least Squares, Dynamic Ordinary Least Squares, Canonical Cointegrating Regression, and Autoregressive Distributed Lag) to provide macroeconomics framework. The data covers the years from 1980 to 2021 for the case of United States and uses income per capita, inflation, employment, population at cities, and number of movie tickets sold as determinants of box office revenues. The results of all regression methods indicate that box office revenue is positively affected by income per capita and movie tickets sold and negatively affected by employment, inflation, and population at cities in the long run.

Keywords: *box office, income per capita, inflation, employment, population*

AMERİKA BİRLEŞİK DEVLETLERİ GİŞE GELİRLERİNİN UZUN DÖNEM REGRESYON DENKLEMLERİNİ KULLANARAK ANALİZ EDİLMESİ

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Özet

Bu çalışma, makroekonomik çerçeve sağlamak için dört farklı eş bütünleşme regresyon modelini (Tam Değiştirilmiş En Küçük Kareler, Dinamik En Küçük Kareler, Kanonik Eş Bütünleşme Regresyon ve Oto-regresif Dağıtılmış Gecikme) kullanarak gişe hasılatını belirleyen faktörleri analiz etmektedir. Veriler, Amerika Birleşik Devletleri örneğinde 1980'den 2021'e kadar olan yılları kapsıyor ve gişe gelirlerinin belirleyicileri olarak kişi başına gelir, enflasyon, istihdam, şehirlerdeki nüfus ve satılan sinema bileti sayısını kullanıyor. Tüm regresyon yöntemlerinin sonuçları uzun vadede gişe gelirinin kişi başına düşen gelirden ve satılan sinema biletlerinden olumlu etkilendiğini ve şehirlerdeki istihdam, enflasyon ve nüfustan olumsuz etkilendiğini göstermektedir.

Anahtar Kelimeler: *gişe, kişi başı gelir, enflasyon, istihdam, nüfus*

INTRODUCTION

The motion picture or film industry is more than hundred years old since it has been made and shown in Paris in 1895 by Louis and Auguste Lumiere (Johnson, 2014), and its development is undoubtedly great and deeper in terms of research and knowledge. Like many other creative industries, movies, as most popular visual art form, are mainly seen as the focus of interest in fields like art, communication, and science. However, all the processes from the planning, production and distribution of the movies to the meeting with the final audience show that their social, economic and cultural impact is undeniable. According to a report written by the National Association of Theatre Owners in 2021, industry has direct economic impacts (in terms of labor income, employment, output, value added, taxes resulting from movie operations) and indirect economic impacts (in terms of labor income, employment, output, value added, taxes resulting from intermediate purchases from local businesses including insurance companies, utility services). Therefore, this is not only limited with regional economy or markets, but also related to world industry. However, Hollywood still dominates the world film industry and much of the film industry's economic analysis deals with Hollywood's hegemony due to the advantage of English as a world language and size of the domestic market as a source of revenue. These advantages also bring economies of scale through having flexible managerial and organizational techniques. This is why the United States has been chosen as a case in the study. As an industry lead body, according to The Motion Picture Association of America (2021), the American film and television industry pays $192 billion wages for 2.2 million jobs by supporting over 110 thousand businesses around the World in 2020. While The US box office market increased by 105% compared to 2020 and reached $4.5 billion in 2021, tickets sales increased by 100% compared to 2020 and reached 470 million.

Film as a significant object for people to entertain and a medium for communities to cultural exchange, is thought to have a significant impact on social cohesion and cultural identities. It is also a sector that provides job opportunities and generates income as mentioned above. From this point of view, what concerns us in terms of cultural economy is whether economic and social forces determine the cultural results such as going to the cinema and watching movies, and therefore the box office revenues.
Lion's share of the studies regarding box office revenues mainly focus on micro analysis covering the customer profile and impact of advertisements and social media (Gazley, Clark, & Sinha, 2011; Redondo & Holbrook, 2010; Irandoust, 2018). Most of the economics analysis are related to cost of production of film industry and its distribution channels (Feng & Sharma, 2016; Fetscherin, 2010; Gaenssle, Budzinski, & Astakhova, 2018; Gazley, Clark, & Sinha, 2011). Some other studies are also related to information systems in film industry that makes predictions for box office revenues by using artificial intelligence methods and big data approaches (Hwang, et al., 2017; Baek, Oh, Yang, & Ahn, 2017; Wang, et al., 2020; Riwinoto, Zega, & Irlanda, 2015). Especially, the machine learning techniques are commonly used in development of prediction algorithms to provide explanations of growth in the field (An, An, & Cho, 2021; Antipov & Pokryshevskaya, 2017; Abidi, Xu, Ni, Wang, & Zang, 2020; Sumod, Premkumar, Jeesha, & Chowdhury, 2021; Ru, Li, Liu, & Chai, 2018; Zhang, Luo, & Yang, 2009; He & Hu, 2021). There are no clear borders between microeconomics and macroeconomics of movies. Classifications of the literature are based on the core focus of the papers, variables used in analysis and methodologies that are conducted. Although, there is subjectivity in grouping the literature in this regard, this paper analyses the impact of macroeconomic indicators on box office revenues by using different econometric models instead of focusing microeconomic variables.

Most of the empirical studies in the literature use film level characteristics and box office data. For example, Addis and Holdbrook (2018) investigates the impact of opening box office, reviewer's ratings and Oscar nominations on consumer's evaluative assessments by using path analysis and concluded that while reviewer's rating has impact on consumer's judgments, other two variables, including opening box office, do not have any effect. Chang et al. (2016) explains the relationship between the audience and the movie showing their favorite star using balance theory and identifies the audience's favorite star as a strong predictor of box office performance. In addition to these, they also find that box office performance is highly correlated with repeat consumption of audiences, movie length, and audience reviews. A study conducted by Feng and Sharma (2016) uses ordinary least squares regression models to explain the relationship between production budget, audience's ratings, cultural context with sales in China and concludes that a rise in production budget leads more sales. Determinants of box office sales of Bollywood and Hollywood in United Kingdom and United States are investigated by Fetscherin (2010) and he identify effects related to product (genre, Motion Picture Association ranking), brand (star power, director power), distribution (season, number of screenings, distributor power) and consumer (audience review) variables by using sample of 330 films. As a result, he concluded that distribution related variables are dominant in the United States, while consumer related variables are dominant in United Kingdom. A very similar study is conducted by Gaenssle et al. (2018) for the case of Russia by considering distribution related factors like budget, brand and star related factors like actors, and source of information like ratings. They found that electronic word of mouth and audience ratings have significant positive impact on box office success in Russia, while they found no star effect. Baek et al. (2017) also analyses the impact of electronic word of mouth on box office revenues by collecting daily data from Twitter, Yahoo!Movies, YouTube and blogs and concludes that Twitter has a greater impact in initial box office revenues due to its high immediacy. Oh, Baek and Ahn (2017) examine the impact of sharing of movie trailers in social media, as a kind of electronic word of mouth, on box office revenue and concluded that sharing of a movie in social media has positive impact on box office revenue, especially in early period of screening than in the later period. Most commonly, the studies in the literature focus on the variables such as star power (Basuroy, Chatterjee, & Ravid, 2003; Fetscherin, 2010; Gaenssle, Budzinski, & Astakhova, 2018; Brewer, Kelley, & Jozefowicz, 2009), genre (Chang & Ki, 2005; Gazley, Clark, & Sinha, 2011; Hwang, et al., 2017; Lee, KC, & Choeh, 2020; Pangarker & Smit, 2013), distribution power (Fetscherin, 2010; Gazley, Clark, & Sinha, 2011), season of release (Basuroy, Chatterjee, & Ravid, 2003; Fetscherin, 2010; Hwang, et al., 2017; Pangarker & Smit, 2013; Lee, KC, & Choeh, 2020; Brewer, Kelley, & Jozefowicz, 2009), audience review (Basuroy, Chatterjee, & Ravid, 2003; Feng & Sharma, 2016; Gaenssle, Budzinski, & Astakhova, 2018; Pangarker & Smit, 2013; Terry, Cooley, & Zachary, 2010; Gazley, Clark, & Sinha, 2011; Ma, Kim, & Lee, 2019), number of screenings (Fetscherin, 2010; Brewer, Kelley, & Jozefowicz, 2009), ratings of Motion Picture Association ratings (Chang & Ki, 2005; Fetscherin, 2010; (Gaenssle, Budzinski, & Astakhova, 2018; Hwang, et al., 2017; Brewer, Kelley, & Jozefowicz, 2009) , awards (Basuroy, Chatterjee, & Ravid, 2003; Simonoff & Sparrow, 2000; Pangarker & Smit, 2013; Terry, Cooley, & Zachary, 2010; Lee, KC, & Choeh, 2020; Brewer, Kelley, & Jozefowicz, 2009), production budget (Basuroy, Chatterjee, & Ravid, 2003; Feng & Sharma, 2016; Gaenssle, Budzinski, & Astakhova, 2018; Pangarker & Smit, 2013; Terry, Cooley, & Zachary, 2010; Brewer, Kelley, & Jozefowicz, 2009) etc. While most of these studies use film level data containing information and statistics about a specific movie to determine box office performance, Gazley et al. (2011), Redondo and Holbrook (2010), Chuu et al. (2009) and Irandoust (2018) employ survey data to model demographic profiles of audiences and their preferences on cinema demand. One of the very recent study conducted by Franses (2021) deal with modeling box office revenues for motion pictures industry by using weekly data and concludes that revenues reach to peak point in the first week and then start decreasing, as expected.

However, some should keep in mind that some variables like audience review, rating of Motion

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Picture Association ratings, awards are usually shaped or finalized after movie is released. Therefore, these are expected to have no effect on box office revenues. Some previous studies (Basuroy, Chatterjee, & Ravid, 2003; Reinstein & Snyder, 2005; Ravid, 1999) also support this argument.

This study differs from the previous studies in some ways. Specifically;

i) As can be seen from the studies in the literature, although related studies make significant contributions on the fields of economics, marketing, consumer behavior, psychology, business and management, some variables as a determinant of box office revenues have not received considerable attention. Admittedly, even the recent studies explore the key determinants of box office by using very similar firm level or demographic level variables. Unfortunately, macroeconomic variables have received less attention in the literature.

ii) In particular, there is a large gap in studies that address issues related to employment, inflation, income per capita etc. Starting from the very early studies in the literature, almost all studies repeatedly focus on the variables like star power, awards, genre, seasonality, word of mouth and timing etc. However, this study investigates the influence of macroeconomic variables on box office revenues rather than making predictions.

iii) Additionally, this study uses four different long run estimation models when analyzing the impact of income per capita, employment, inflation, urban population and ticket sold on box revenue to increase reliability of results obtained from regressions and check the robustness of results. Simply, regression is a most commonly used statistical method, especially in economics and finance, that tries to determine the relationship between one dependent variable (which is the box office revenue in this study) with series of independent variables (which are income per capita, employment, inflation, population at cities, and ticket sold in this study).

The rest of the paper is organized as follows. The data and variables will be explained and described with the methodologies used in the study. Then, the results obtained from different estimation methods will be given and discussed. Finally, the paper discusses with its limitations and further policy and research directions as well as the overall contribution of the study will be discussed.

DATA AND THEORETICAL FRAMEWORK

The study uses yearly data from 1980 to 2021 to analyze the impact of income per capita as dependent variable by using inflation, employment, urban population and ticket sold as control variables on box office revenues of United States. While data excluding box office revenues and ticket sold were obtained from World Bank World Development Indicators database, remaining data is obtained from the Statista web site. The function used in the study can be briefly shown as follows.

$$boxrev = f(gdppc, employ, inf, popcity, ticket)$$

Eq. 1

$boxrev$ is dependent variable and represents the box office revenue in US in billions US$. Independent variable is as a measure of growth and indicates GDP per capita (constant 2015 US$). E is defined as the employment ratio above the 15 years old. is GDP deflator showing the rate of price change in the economy as a whole. is used as a measure of urbanization and show population in largest cities. And finally, is the number of movie tickets sold in US (in billions US$). We used the logarithmic form of each variable to obtain their elasticity estimates indicating the expected percentage change in dependent variable, which is box revenue, when there is 1% change in other independent variables. The model specification is given as follows.

$$Lboxrev_t = \beta_0 + \beta_1 Lgdppc_t + \beta_2 Lemploy_t + \beta_3 Linf_t + \beta_4 Lpopcity_t + \beta_5 Lticket_t + \varepsilon_t$$

Eq. 2

METHODOLOGY

The aim of the study to examine the impact of chosen macroeconomic variables on box office revenues in USA. The brief description of the variables used in the study is given in Table 1. Standard deviations of all variables are very low. The value of skewness is between -0.5 and 0.5 for LGDP, LEMPLOY, LINF, LPOPCITY. It indicates that the data is nearly symmetrical. However, while LTICKET is negatively skewed (due to -3.95<-1), LBOXREV is slightly negative skewed (due to -0.92 is between -1 and -0.5). Insignificant values of Jargue-Bera indicates that variables are normally distributed at 5% level, except for box revenue (Lboxrev) and ticket sold (Lticket).

First of all, it is important to check the stationarity of variables before we conduct cointegration test. The study uses Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test, which are most well-known stationarity tests. The null hypothesis checks the availability of unit root (non-stationarity) against the stationarity of data. The results of test are provided in Table 2. According to the results, even if the variables have unit roots in their level, all are stationary in their first differences.

Next, Johansen Cointegration Test was employed to check the availability of long-term relationship between variables. As given in Table 3, while trace test indicates 4 cointegration equations at the 5% significance level, maximum eigenvalue test indicates 3 cointegration equations. After the cointegration among variables is confirmed with these results, as given in Table 3, we estimated the long run coefficient of variables by using Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), Canonical Cointegrating Regression (CCR), Autoregressive Distributed Lag (ARDL). These models are preferred to ordinary least squares because they take the leads and lags of the first differences of regressors to prevent endogeneity bias and small sample bias. The FMOLS, DOLS, CCR, and ARDL estimation use Bartlete kernel, Newest-West fixed bandwith of 4.000. While DOLS uses 1 as leads and lags, ARDL model is chosen as (1,0,0,0,0,0) by using automatic selection. Model selection method for ARDL is Akaike info criterion (AIC) and ARDL uses 1 as lag of regressors. The results of estimations are given in Table 4.

EMPIRICAL RESULTS

Unit root results ensure that none of the variables are integrated of order 2. After confirming the availability of cointegration among variables, different cointegration models used to check the robustness

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of the results. The results from different methods provides similar coefficient estimates and same signs with minor differences. Concluding remarks and detailed interpretations are given below.

Box office revenues generated from the demand for movie industry and therefore, classic economic theories are applicable to this industry as applied to other industries. Namely, consumers demand more of good when there is increase in their income, if the good is normal good. Here, we assume that watching movie as an entertainment activity is a normal good and people will prefer more of movie watching in the case of having higher income level. GDPPC is used as an indicator of income in the study, instead of using personal disposable income. Briefly, the sign of GDPPC is expected to have significant positive value, as $(\beta_1 = \frac{\partial Lboxrev}{\partial Lgdppc} > 0)$, that leads higher box office revenues. Because, increase in income level allows people to purchase more (normal) goods, including movie watching, and in turn to earn more box office revenues. According to the estimation results given in Table 4, the coefficient of LGDPPC is calculated as 3.736 (p=0.000), 1.766 (p=0.000), 3.612 (p=0.000), and 3.397 (p=0.000) in FMOLS, DOLS, CCR and ARDL models respectively. The positive coefficient sign of GDPPC reveals that an increase in income per capita will increase box office revenues, as expected. In addition to these, all coefficients are higher than 1 and this indicates that box office revenues are highly responsive to the income changes. For example, according to the result obtained from FMOLS, 1% increase in GDPPC results in 3.73% increase in box office revenues. Similar interpretations can be done for other LGDPPC coefficients obtained from the models used in the study.

Employment is used as another determinant of box office revenues. It is clear that the availability of time is a precondition for joining entertainment activities but it is a scarce resource, especially the people are employed. People have limited free time after deducting the hours for work and for subsistence, such as sleeping and eating. However, the time remaining has cost in terms of alternative opportunities forgone. For example, watching a movie means that the consumer will spend at least 90 minutes of their time to attend that event. Therefore, the time spend in cinema to watch a movie can be defined as the opportunity cost for those who have other attractive and less costly opportunities, such as earning money. Therefore, we expect that E$mploy$ will have negative significant sign, as $(\beta_2 = \frac{\partial Lboxrev}{\partial Lemploy} < 0)$. The opportunity cost of watching a movie depends not only on the time actually spent in a cinema, but also on how much time is needed for the factors such as transportation, location, parking and so on. The increase opportunity cost of time for working people tend to offset the spending leisure time. However, we need to mention that there is a clear paradox on the leisure. Namely, aggregate spending on entertainment is mostly done by middle age groups although their majority have relatively limited time due to long working hours. At this point, availability of income can play an important role for middle age groups compared to young people. The coefficient of $Lemploy$ is calculated as -1.389 (p=0.026), -1.571(p=0.000), -1.388 (p=0.029), and -1.447 (p=0.007) in FMOLS, DOLS, CCR and ARDL models respectively. These results indicate negative relationship between employment and box office revenues, as expected and explained above. Simply put, according to the results obtained from FMOLS and CCR, 1% change in employment results in an inverse change of 1.3% in box office revenues. This change is calculated as 1.5% in DOLS and 1.4% in ARDL. These results support the leisure time argument for movie watching, as detailed above.

Inflation as another explanatory variable is used as a determinant of box office revenues and indicates increase in overall price level in the country. It also means that if there is increase in inflation level of the country, it also indicates increase in price of movies in theaters. According to demand theory, increase in the price will lead decrease in the quantity demand of good, which is movie demand here.

However, change in revenue does not only depend on price, but also the quantity sold. Here, change in revenue is determined by the amount of changes in quantity and price. Namely, when increase in price is higher than the decrease in quantity, price effect will offset the changes in quantity and revenue increases in turn $(\beta_3 = \frac{\partial Lboxrev}{\partial Linf} > 0)$, or vice versa. The price elasticity of demand is defined as inelastic in this case. In some cases, increase in price may lead decrease in quantity at the same amount that results in no change in revenue $(\beta_3 = \frac{\partial Lboxrev}{\partial Linf} = 0)$. This is defined as unit elastic demand. And finally, amount of increase in price can be less than the decrease in quantity and it brings decrease in revenue $(\beta_3 = \frac{\partial Lboxrev}{\partial Linf} < 0)$, which is known as elastic demand. When we have a look at the estimation results, estimated value of the coefficient of inflation is -0.226 (p=0.000) in FMOLS, -0.050 (p=0.015) in DOLS, -0.220 (p=0.000) in CCR, and -0.210 (p=0.007) in ARDL models. The sign of inflation is negative and highly significant in all regression. These outcomes show robustness of results and indicate increase in price by 1% leads decrease in box office revenue by 0.22%. Therefore, we can conclude that demand of movie is elastic, which means consumers are responsive to price changes in movie market.

Population, especially the population living in cities, is also used as a determinant of box office revenues. Increase in population leads to an increase demand for movies and box office revenues in turn. Population in large cities can be seen as an indicator for urbanization. Haupert (2006) explains the impact of urbanizations on entertainment industry, including movies, in two ways: i) farmers live in rural areas and work more hours than the people living in urban areas, and ii) non-farm workers live predominantly in urban areas and earn higher wages than farmers. In addition, urbanization reduces the cost of pursuing entertainment, as venues and theaters close to each other and access to entertainment products such as movies in theaters are easier. Therefore, the sign of population variable is expected to have positive significant value, as $(\beta_4 = \frac{\partial Lboxrev}{\partial Lpopcity} > 0)$. However, while the estimated coefficient of Lpopcity has negative significant sign in FMOLS and CCR , it is insignificant in DOLS and ARDL models. These results contradict the explanations given above. From this, it is seen that the 1% increase in the population living in big cities causes a 5.14% decrease in box office revenues according to FMOLS and a 4.79% decrease according to CCR. The decrease in box office revenues caused by urbanization can be explained in the following ways; i) people living in cities have easy access to different leisure time activities, ii) reducing the opportunity cost of time through online platforms such as Netflix, iii) for those who want to experience the cinema outside of the physical space, the existence of simultaneous screening environments and easy access to technologies that support reaching these environments in cities.

Instead of using the movie ticket price, the study uses the number of movie tickets sold in US (in millions). Vogel (2020) mentions that ticket sales are less responsive to the changes in box office prices, but more responsive to income and total cost of movie going, including transportation, parking, restaurant meals etc. Because, the price or the entrance fee does not change and is fixed during the shows. Therefore, with a fixed entry price, any change in box office revenue is due entirely to the number of entries (Ginsburgh & Throsby, 2006, p. 625). We expect positive impact of ticket sold on box office revenues, as $(\beta_4 = \frac{\partial Lboxrev}{\partial Lticket} > 0)$. According to the results obtained from the study, the number of floors for the number of tickets sold was calculated as 1.051, 1.004, 1.055, and 1.063 in FMOLS, DOLS, CCR and ARDL models, respectively. All coefficients are positive as expected and have very high significance with p=0.000 value. Under the assumption of ceteris paribus holding all other factors constant, increase in movie tickets sold result in increase in box office revenues. The movies are part of the creative industries as one of the tool of performing arts and shown in a specific fixed times in cinemas. Therefore, this revenue cannot be

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generated if the theater has unsold seats at the time of the film's released. Because, Americans do not view films by only going cinemas and use some other platforms such as internet, home videos, mobile contents, televisions etc., as substitutes.

CONCLUSION

This study analysis the impact of some macroeconomic variables, such as income per capita, inflation, employment, population at cities and movie tickets sold, rather than focusing micro level data, on box office revenues. To achieve this aim and check the robustness of results, the study employ four different long run econometric models, namely known as FMOLS, DOLS, CCR and ARDL. The results of econometric methods are consistent and are summarized below.

i) The cointegration test proves long run relations between box office revenues and income per capita, inflation, employment, population at cities, movie ticket sold.

ii) In the long run, box office revenue is positively affected by income per capita and movie tickets sold.

iii) In the long run, box office revenue is negatively affected by employment, inflation and population at cities.

iv) Elasticity of income per capita is greater than 3 in FMOLS, CCR and ARDL models, while it is greater than 1 in DOLS.

v) Elasticity of inflation is between –1 and 0 in all regressions.

vi) Elasticity of employment is between -2 and -1 in all models.

vii) Elasticity of population at cities is between -4 and -5 when it is significant in regressions.

viii) Elasticity of ticket sold is greater than 1.

ix) The results of FMOLS, DOLS, CCR, and ARDL methods are robust and consistent with each other.

In terms of policy implications, The United States of America should lower overall price levels, including movie ticket price, to increase the box office revenues. The policy or decision makers should adopt growth policies to increase income per capita. Furthermore, movie watching is a leisure activity, different time and price policies should be adopted to give flexibility to working people. Interestingly, population at cities results in decreases in box office revenues. Therefore, increasing the number of movie theaters in rural areas can bring additional income and opportunities for businesses. As mentioned above, different online platforms, such as Netflix, Amazon Prime Video, Disney Plus, and Paramount Plus have also an impact on USA box office revenues, as movie substitutes. The substitutes are not only limited to these, but internet protocol TVs (IPTV), such as YouTube, Falcon TV, Select TV, can also be considered as an alternative to cinemas. The impact of availability or improvement in the technology can be the main focus of another study related to box office revenues. In addition, alternative leisure activities and easy access to technology in urban areas also negatively affect box office revenues. For this reason, investments to be made for rural areas, which have the opportunity to participate in less artistic activities, may bring an increase in box office income. As expected, the increase in the number of tickets sold also increases the box office revenues. For this reason, the fact that the tickets are accessible not only from the box office at the cinema entrance, but also from different platforms will increase the sales. For example, online sales options can be increased or different promotions can be offered in addition to the ticket purchased.

At the time of writing, there is an ongoing impact of the COVID-19 on movie industry, although its long term impact remains unknown, beyond the immediate impacts. Consumers are still protective and unwilling to go theatres. This study ignores the Covid-19 period due to the structural changes in the industry. Therefore, further studies are recommended to measure the impact of unexpected crisis on the industry by covering all dimensions including production and distribution.

As can be seen from the studies mentioned in the literature, movie related publications mostly focus on specific dimensions of movies and consumer habits and their determinants. However, all these publications are less about general economic impacts of movies and cultural economics. Marketers and managers mostly focus on core subject matters like production and distribution, while psychologists try to understand psychological incentives and habits of people while choosing movies. In addition to research conducted all these fields, economical contribution of movie industry should be analyzed with empirical works to emphasize the importance of movie industry on economies of societies. Therefore, data availability is crucial to be able to conduct empirical studies in unexplored areas of the field.

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Table 1. Descriptive Statistics

	LGDPPC	LEMPLOY	LINF	LPOPCITY	LTICKET	LBOXREV
Mean	4.660830	1.785387	0.364829	7.239738	3.078256	0.773951
Median	4.687853	1.788875	0.341118	7.251408	3.109681	0.848036
Maximum	4.787322	1.808886	0.975990	7.274679	3.197498	1.075182
Minimum	4.488204	1.754119	-0.193173	7.193164	2.345883	-0.036212
Std. Dev.	0.089963	0.014959	0.236196	0.029167	0.140360	0.266107
Skewness	-0.433690	-0.212222	0.400597	-0.365866	-3.957269	-0.921205
Kurtosis	1.941069	1.821035	3.765289	1.546288	20.00152	3.390281
Jarque-Bera	3.278941	2.747696	2.148264	4.635244	615.4604	6.206891
Probability	0.194083	0.253131	0.341594	0.098508	0.000000	0.044894

Table 2. Unit Root Test Results

		Level		First Differences	
	Variables	intercept	intercept&trend	intercept	intercept&trend
ADF	LGDPPC	-1.57908(0)	-1.48631(0)	-5.46178***(0)	-5.61958***(0)
	LEMPLOY	-1.42439(0)	-1.66624(0)	-5.55854***(0)	-5.71925***(0)
	LINF	-3.22058**(0)	-3.01978(0)	-6.04115***(1)	-6.39867***(1)
	LPOPCITY	-1.95115(1)	-2.15328(1)	-1.22576*(0)	-1.66194(0)
	LTICKET	-2.77199*(0)	1.23443(2)	-8.65912***(0)	-3.71209**(1)
PP	LGDPPC	-1.86121(6)	-1.46212(3)	-5.43719***(2)	-5.49629***(5)
	LEMPLOY	-1.42439(0)	-1.68458(3)	-5.55698***(2)	-5.64440***(4)
	LINF	-3.08120**(8)	-2.47722(7)	-4.87871***(13)	-6.55017***(25)
	LPOPCITY	-1.23675(5)	-0.63009(5)	-1.45993*(2)	-1.78764(1)
	LTICKET	-2.77199*(0)	1.23443(2)	-8.65912***(0)	-9.18207***(1)

Notes: *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% levels, respectively. (Source: Authors' results.)

Table 3. Johansen Cointegration Test Results

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.988629	288.4605	95.75366	0.0000
At most 1 *	0.686577	109.3923	69.81889	0.0000
At most 2 *	0.510939	62.98425	47.85613	0.0010
At most 3 *	0.376934	34.37352	29.79707	0.0139
At most 4	0.319495	15.44941	15.49471	0.0508
At most 5	0.001315	0.052632	3.841465	0.8185

Trace test indicates 4 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.988629	179.0682	40.07757	0.0000
At most 1 *	0.686577	46.40806	33.87687	0.0010
At most 2 *	0.510939	28.61073	27.58434	0.0368
At most 3	0.376934	18.92411	21.13162	0.0991
At most 4 *	0.319495	15.39678	14.26460	0.0330
At most 5	0.001315	0.052632	3.841465	0.8185

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

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Table 4. Estimation results of Cointegration Equation Models

Method: Fully Modified Least Squares (FMOLS)						
Variable	Coeff.	Std. Error	t-Statistic	Prob.		
LGDPPC	3.73625	0.51033	7.32126	0.00000	R^2=0.9442	Mean dep.var. =0.7874
LEMPLOY	-1.38997	0.59963	-2.31804	0.02640	Adj.R^2=0.9363	S.D. dep.var.=0.25441
LINF	-0.22636	0.04059	-5.57655	0.00000	S.E. of reg.=0.0641	Sum suq. resid=0.1442
LPOPCITY	-5.14305	1.60081	-3.21278	0.00280	Long-run variance=0.0019	
LTICKET	1.05118	0.06017	17.46987	0.00000		
C	19.91967	9.75360	2.04229	0.04870		
Method: Dynamic Least Squares (DOLS)						
LGDPPC	1.76677	0.26182	6.74794	0.00000	R^2=0.9990	Mean dep.var. =0.8120
LEMPLOY	-1.57172	0.30326	-5.18269	0.00010	Adj.R^2=0.9979	S.D. dep.var.=0.2217
LINF	-0.05066	0.01884	-2.68907	0.01500	S.E. of reg.=0.0100	Sum suq. resid=0.018
LPOPCITY	0.81279	0.80356	1.01148	0.32520	Long-run variance=0.0000	
LTICKET	1.00407	0.08756	11.46681	0.00000		
C	-13.58343	4.84505	-2.80357	0.01170		
Method: Canonical Cointegrating Regression (CCR)						
LGDPPC	3.61563	0.51226	7.05819	0.00000	R^2=0.9447	Mean dep.var. =0.7874
LEMPLOY	-1.38872	0.61123	-2.27203	0.02930	Adj.R^2=0.9368	S.D. dep.var.=0.2544
LINF	-0.22029	0.04529	-4.86424	0.00000	S.E. of reg.=0.0639	Sum suq. resid=0.1430
LPOPCITY	-4.79603	1.56593	-3.06274	0.00420	Long-run variance=0.0019	
LTICKET	1.05599	0.07789	13.55805	0.00000		
C	17.95098	9.54643	1.88039	0.06840		
Method: Autoregressive Distributed Lag (ARDL)						
LBOXREV (-1)	-0.03675	0.11841	-0.31037	0.75820	R^2=0.9457	Mean dep.var. =0.7874
LGDPPC	3.39789	0.83471	4.07073	0.00030	Adj.R^2=0.9361	S.D. dep.var.=0.2544
LEMPLOY	-1.44794	0.50728	-2.85431	0.00730	S.E. of reg.=0.0642	DW= 1.8505
LINF	-0.21097	0.13534	-1.55888	0.12830	Long likelihood=58.1822	
LPOPCITY	-3.78148	2.29028	-1.65110	0.10790		
LTICKET	1.06348	0.07505	14.17061	0.00000		
C	11.73043	12.86186	0.91203	0.36820		