Effects of Industrial Protection Policies on Firms' Incentives and Consumer Welfare

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Abstract. Industrial protection policies have been widely implemented to protect domestic firms from foreign competition. This project specifically focused on examining the effects of the Domestic Movie Protection Month Policy that started in China in 2014. First, I demonstrated the existence of this policy by measuring the obvious delay of foreign movies during the summer (July and August) after 2014. Second, I compared the quality of domestic movies released during the summer (treatment group) with movies released at other times of the year (control group) to evaluate the effect of the policy. Two proxies for movie quality and consumer welfare were constructed for robustness checks: (1) Douban rating, which is the general rating of the entire population of the audience on Douban website, the biggest movie rating website in China; (2) Welfare Index which is based on the sentiment analysis constructed by the NLP (Natural Language Processing) of around 70,000 consumers' comments. The final result showed that the Douban rating and Welfare Index were both significantly higher for domestic movies released during the summer after 2014 than before 2014, while the quality of movies in the control group remained unchanged. This finding supports the hypothesis that domestic firms will have more incentives to invest in quality upgrading if the industrial protection policy is implemented. This conclusion also adds to the recent heated discussions on whether policymakers shall continue to implement industrial protection policy not only in the movie industry but also in other industries that face severe foreign competition.

Keywords: Industrial Protection Policies; Chinese Movie Industry; Natural Language Processing (NLP); Sentiment Analysis; Consumer Welfare; Difference-in-Difference (DID).

1. Introduction

In recent decades, industrial protection policy has been a heated topic. China and many other countries have been implementing tariffs or import quotas in several industries to protect domestic firms, especially in production sectors like the automotive industry. With wide discussions on cultural walls recently, we then start to think about the specific impacts of setting protection policies in the cultural industry.

Therefore, the paper aims to measure the consumer welfare impact of industrial protection policies on domestic firms' incentives of product quality upgrading, using evidence from the movie industry in China and the method of Natural Language Processing (NLP). Since 2014, China has implemented the Domestic Movie Protection Month Policy: only domestic movies can be shown during the summer break. Most other protection policies are in traditional production industries, but this policy shows that we can also set such actions in the culture and entertainment industry. Therefore, it is important to look at the consumer's feedback on the policy.

To examine the effects of this policy, we collected massive data, including box office, rating, release date, comments, etc, from Douban Website, which is a Chinese movie rating and review website like Rotten Tomato, to form a data set. Using the data set, we first demonstrated the existence of the policy and showed that the policy indeed happened after 2014 in the summer. Then, we set two proxies for consumer welfare and movie quality: Douban Rating and the Welfare Index. Douban rating is the weighted average of the audience rating on the Douban Website, representing the general opinion of the population. However, this could be possibly manipulated by companies using robots and fake accounts. Therefore, we used the Welfare Index as well. The Welfare Index is derived from the sentiment analysis of the comments of the movies using Natural Language Processing (NLP), reflecting the consumer welfare of the audience. The Welfare Index is less likely to be manipulated and could represent the actual feedback of the audience because it is derived from the top 40 comments of each movie based on popularity, which means the comments are liked and agreed by most consumers. To further examine the effects of the policy, we used the Difference in Difference method for both Douban Rating and Welfare Index. We set two dimensions: whether the group is targeted by the policy in a year and whether the group is before or after the policy change: (1) Other time of the year (Control Group) Before Domestic Movie Protection Month Policy; (2) Summer: July and August (Treatment Group) Before Domestic Movie Protection; Month Policy; (3) Other time of the year (Control Group) After Domestic Movie Protection Month Policy; (4) Summer: July and August (Treatment Group) After Domestic Movie Protection Month Policy. Using the Difference in Difference, we eliminated the possibility of pre-trend effects and zero-sum bias. The results of both proxies support that the domestic firms are provided with more opportunities to grow and given more incentives to invest in quality upgrading and indicating the increase in consumer welfare in general.

However, there is also a surprising finding of a spillover effect that only happened in the Welfare Index group. This could happen mainly because there are no pure control groups in my setting. Even though movies in other months of the year are not affected by this protection policy, they are all in the same movie market and there can be competition forces that exert either positive or negative externality/spillover on those months. Therefore, as a future step, we are considering building models to model the market competition forces directly and estimate the extent of externality. There are also other potential improvements to be done. For example, we can collect more data for comments to construct a more precise Welfare Index. For this time, we only collected 40 comments from each movie because my hardcore limitation did not allow me to run massive data. Also, our research has some important applications. First of all, the results directly provide support to policymakers on the implementation of industry protection policies in the movie industry and even in a broader context. In addition, we have used computational method like NLP and sentiment analysis to construct a factor for an economic problem, and this can be a growing field in the future, especially considering the massive data set available now online.

In section II, we will discuss the relevant literature and their findings. Section III introduces more details of the policy and context. In Section IV, we will discuss the hypotheses and mechanisms. Section V shows the data and methods, and Section VI presents empirical results. Section VII draws the conclusion, and section VIII discusses the further studies and possible application of the finding. Section IX gathers all the Figures and Tables that are presented and mentioned in the paper.

2. Literature Review

2.1 Industrial Protection Policies

There is a large literature analyzing the impact of industrial protection policies both theoretically and empirically. Industrial protection policies, like tariffs, subsidies, and quotas, restrict international trade to protect domestic companies from foreign competitors [1]. These policies allow the domestic industries to avoid competition with strong foreign counterparts, so the domestic industries will have more opportunities in the market and develop quickly [2]. However, Harrison and Rodr´ıguez-Clare (2010) found that the protection policies may also harm the domestic industries because the domestic industries tend to have less incentive to develop products with higher quality when the pressure of the competition is minimal. Also, the effects of Industrial Protection Policy could be futile and the market failure would not be fixed if the market failures exist mainly because of coordination failure within specific industry. Although the literature found that industrial protection policies provide more opportunities and capital in the domestic market, whether firms would use those resources to further invest in product quality remains unknown. Therefore, our paper aims to answer this question: whether the firms would have incentives to upgrade their product quality when the Industrial Protection Policy is implemented. Empirical results from previous literature showed the total productivity and product growth boosted by the increased competition within the industry, when the all the medium and large companies in China received a subsidy protection policy [3]. Because the effects of industrial protection policies vary cases by cases as the literature shows, we formulated a hypothesis with two different mechanisms based on different theories.

2.2 Application of Natural Language Processing

Previous researchers used Natural Language Processing Machine Learning models to conduct sentiment analysis on the consumer review to understand the public opinion on their products. As social media has dominant basically everyone's daily life, many people are eager to share their feelings and thought through comments on social media [4]. Therefore, evaluating the consumer review using sentiment analysis is very important. Day Et al. note that the analysis evaluates the rating of products. Also, the study states that categorizing the comments into positive, negative, and neutral is important because neutral comments merely only convey opinions with no sentiment or even basic facts. This is very important in our study because the neutral comments could compromise the preciseness of the Welfare Index, if neutral messages are compulsively identified as either positive or negative for the sake of categorization. Moreover, a study of restaurant reviews applied sentiment analysis to evaluate both the service of the restaurant and the experience of the consumer, intending to achieve a win-win situation for the server and consumer and aim for the maximum of economic benefit [5]. Another study used Natural Language Processing to evaluate the comments reviews for the Amazon product, and the researchers found the preference of the product and what characters is most directly related to the rating of the products [6]. Although these studies investigated in different industries, they all share some similarities for the application of NLP: NLP is used to reflect the quality of the service or product and the experience of the consumer. Based on this, we use Welfare Index, which is derived from the comments using NLP, as a proxy for movie quality and consumer welfare.

To perform the Natural Language Processing for the comments, we used the RoBERTa model. A group of computer scientists improved the BERT model, which is a pretraining approach of measuring the impact of many key hyper-parameters and training data size, into a new model named as RoBERTa, and the new emerged RoBERTa model have several advantages: 1) it could train the model for a longer period, process more data with bigger batches; 2) it removes the next sentence prediction; 3) changing the pattern applied to the training data [7]. With these advantages, the RoBERTa model could even outdo the post-BERT models. Not only for these advantages, we choose to use this model because it does not merely set a binary classification loss, which allows us to assess comments that could be positive, negative, or neutral. Using the RoBERTa model, we could formulate a pretty precise and convincing Welfare Index that reflects the consumer welfare from the comments in Douban.

3. Contexts

In this paper, we specifically examine the Industrial Protection Policy in the Chinese Movie Industry called Domestic Movie Protection Month. Domestic Movie Protection Month restricts the most of the release of foreign movies, and basically only domestic movies are allowed to be shown during the summer, July and August. Because the majority of the consumer in the industry are teenager students and young white-collar worker, the release in summer is one of the most important and profitable periods in the year. Therefore, this policy is intended to protect the domestic movie firms from competitive foreign counterparts by providing the domestic companies with more opportunities in the market. Domestic Movie Protection Month is never published announced by the government or the relevant department, but the action of the government that promote domestic movies implicitly supports such policy. In Section 6.1, we demonstrate the existence of the policy and indicates that the policy indeed is implemented since 2014 during every summer. The policy would exist if the number of foreign movies shown during the summer are significant lower and the delay in the domestic release of foreign movie is significantly longer. Current literature on this policy generally showing a negative review. For example, Zhou (2015) noted that Chinese government tried to promote the domestic movie with protection policy [8], but the policy actually led to an unintended negative effect: compromising the pluralism, which could help increase the creativity and influences, in the domestic market. Also, China decreased the portion of imported films from Hollywood, but Hollywood movie still capture 30% to 50% of the market, evidencing from the box offices [9]. However, box office is not the only factor to examine the effect of the policy. Feng (2019) suggests that box office is an insignificant predictor of consumer welfare [10]. Therefore, we will examine the policy using consumer welfare as a proxy for movie quality, intending to check if the policy also hampers the consumer feedback. It is difficult to evaluate the consumer welfare because movies are performance good, of which consumer's preference varies over time [11]. Therefore, we apply Natural Language Processing to examine the comments to reflecting a relatively precise consumer welfare impact.

4. Hypotheses and Mechanisms

Based on the literature review and context, we found controversial views on the effects of the industrial protection policy, so we set a hypothesis based on different mechanisms, each of which represents a premise.

Hypothesis: The Industrial Protection Policy affects (either increases or decreases) domestic firms' incentives of product quality upgrading and consumer welfare through different mechanisms.

Mechanism A: If industrial protection policies provide domestic firms with opportunities to grow, then domestic firms will have more incentives to invest in quality upgrading and consumer welfare will increase when the Domestic Movie Protection Month Policy is implemented.

Mechanism B: If industrial protection decreases a lot of competition from foreign products, then domestic firms will have fewer incentives to invest in quality upgrading and consumer welfare will decrease when the Domestic Movie Protection Month Policy is implemented.

5. Data and Methods

5.1 Data

We built a data set based on data-scraping from Douban Website. Douban Website is a Chinese movie review and rating website, similar to Rotten Tomato in the US. Douban website provide the basic information about the movie, including production country, release time both in China and abroad, box offices, consumer rating, and comments. Using this information to construct a data set, we could classify the movies into different groups. For example, we split the movies into domestic and foreign groups based on the production location: the movie will be labeled as domestic if the production location is in China mainland, and the movie will be labeled as foreign if the production location is outside of China, which also includes Hong Kong and Taiwan. In addition, using the release time both in China and abroad, we could calculate the delay in releasing the foreign movies in the domestic market, and the delay helped us to demonstrate the existence of the Domestic Movie Protection Month. The Douban rating, which is the consumer rating constructed by Douban, is one of the two important proxies for the consumer welfare in this research. The rating is weighted average from millions of individual consumer's ratings, representing the general opinion of the population. We also collected the comments of the movies to derive the Welfare Index, using Natural Language Processing and sentiment analysis. The detailed procedure of NLP will be explained in Section 5.2. Both the Douban Rating and the Welfare Index were constructed as proxies for consumer welfare and movie quality to examine the effects of the Domestic Movie Protection Month Policy.

There are some differences between Douban Rating and the Welfare Index. Douban rating represents the general opinion of the population, but it can possibly be manipulated by reviews of computer robots and fake accounts that are hired by the movie company or extreme fans. The Welfare Index was derived from the top 40 comments based on the popularity in the movie review of each movie. The top 40 comments guarantee that the Welfare Index reflects only the actual feedback from the audience and examines consumer welfare from a different dimension than that of the Douban Rating. Therefore, both Douban Rating and Welfare Indexes were used to analyze the effects of industrial protection policy on movie quality from different dimensions to maintain more robust results. For this research, movie year-lists from 2009 to 2018 in Douban were used. Together, a total of 1710 movies and 69,528 comments of those movies (approximately 40 from each movie) were used.

5.2 Welfare Index & Natural Language Processing (NLP)

The Welfare Index, which we nominated, results from the sentiment analysis on the consumer review, reflecting the consumer welfare of the product. the Welfare Index was derived from the top 40 comments based on the popularity in the movie review of each movie. We used the RoBERTa (A Robustly Optimized BERT Pretraining Approach) model to conduct the sentiment analysis for the comments for the movie and derive the Welfare Index. First, all comments were pre-processed: dropping null values, cleaning stopwords, and conducting segmentation. Then these comments were vectorized based on the RoBERTa model. Then a subset of comments was selected and given ground truth (i.e., manually annotating Welfare Index score for each comment). Afterward, these annotated comments were split into three sets, training set, validation set, and test set, to build a predictive model (i.e., classifier) to infer the Welfare Index for the rest of unselected comments: we trained several predictive models with different hyper-parameters based on vectorized comments in the training set. Then, the validation set was used to select the best performing classifier. Besides, the test set examined the accuracy of the best performing classifier by comparing the predicted results with ground truth, which estimated the performance of the classifier in a real-world scenario. Lastly, the trained classifier was applied to the rest comment to predict their Welfare Index. The Welfare Index of the movie was predicted by this trained classifier based on the comments. The scale of the Welfare Index varies from 0 to 1, where 0 means minimal consumer welfare and 1 means maximal consumer welfare.

As Table 1 shows, the validation data set shows an accuracy of nearly 85% with more than 300 sample comments; as Table 2 shows, the test data set even shows a greater accuracy of 90% with more than 3000 sample comments. Table 3 provides 5 comments from Douban and their Welfare Index, showing the extent of Welfare Index's ability to reflect the true sentiment of the comments. For example, the praising comment with comment id 7528 says that "AWESOME! I have seen my adrenal hormone outbreak!!!" and it has a high Welfare Index of 0.963. In contrast, a disappointed comments with comment id 10528 says that "I wiped a rubbish, the characters were so bad, the plot was also forced..." and it receives a low Welfare Index of 0.111. Having a moderate comment, comment with comment id 8497 has a Welfare Index of 0.674, which is corresponded with its sentiment. There is a total of 69,628 comment in the data set, and they are all in Chinese. Table 3 only demonstrates 5 comments that are already translated for a convenient purpose for the reader. To check all the original comments, please check the data book.

Table 1. Assessment of the performance of the model on the validation data set.

Accuracy: 0.8492307692307692				
	precision	recall	f1-score	support
0	0.72	0.62	0.66	78
1	0.88	0.92	0.9	247
accuracy			0.85	325
macro avg	0.8	0.77	0.78	325
weighted avg	0.84	0.85	0.85	325
Confusion Matrix				
Predicted	0	1	All	
TRUE				
0	48	30	78	
1	19	228	247	
All	67	258	325	

Table 2. Assessment of the performance of the model on the test data set.

Accuracy: 0.8974436090225564				
	precision		precision	
0	0.85	0	0.85	0
1	0.91	1	0.91	1
accuracy		accuracy		accuracy
macro avg	0.88	macro avg	0.88	macro avg
weighted avg	0.9	weighted avg	0.9	weighted avg
Confusion Matrix		Confusion Matrix		Confusion Matrix
Predicted	0	Predicted	0	Predicted
TRUE		TRUE		TRUE
0	730	0	730	0
1	128	1	128	1
All	858	All	858	All

Table 3. 5 comments from Douban and their Welfare Index. There are a total of 69,628 comments in the data set, 5 of them are shown here as examples. Comments were originally in Chinese, and they are translated into English with auto translate with google translate. A full list of the comments and the data set are included in the data book.

comments (translated)	cid	id	Welfare Index
This is OK, the story narrative is also, the child can take a look.	67678	30208005	0.9188635
AWESOME! I have seen my adrenal hormone outbreak! ! !	7528	4286017	0.96359855
I have never seen such an anti-war film, real interpretation, and true touch.	37894	5031409	0.9918657
I wiped a rubbish, the characters were so bad, the plot was also forced...	10528	10727042	0.1107349
The rabbit man is very funny, it is a bit mean, and it is good to see it.	8497	5337555	0.6744152

We also ran regressions between the Welfare index and the Douban rating to examine their correlation. The Welfare Index is positively correlated with each movie's Douban Rating, as both the Figure 1 and Table 4 show. However, they are not perfectly linear with each other and the residual of the correlation is moderate, 0.5831. This residual of the correlation further suggests that Welfare Index examines the consumer welfare from a different dimension than the Douban Rating does. Therefore, using both indexes for analysis can help consolidate the final results and draw a more robust conclusion.

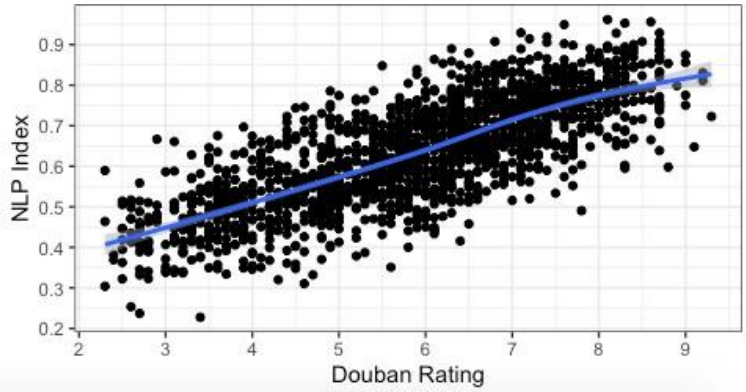

Fig. 1 A moderate positive linear correlation between Douban Rating and Welfare Index of the movies. Each point represents a movie and there are a total of 1705 movies presented.

Table 4. Summary of the correlation between Douban Rating and Welfare index of the movies.

Regression Statistics	
Multiple R	0.7637
R^2	0.5833
Adjusted R^2	0.5831
Standard Error	0.0845
Observation	1705

5.3 Data Analysis: Difference-in-Difference (DID) & T-Test

We employed the Difference-in-Difference approach examine the effects of the Domestic Movie Protection Month on the consumer welfare and firm's incentives. Difference-in-Difference is a classical econometric method that has been widely used to measure various policy effects. The main rationale behind the method was to find two groups: control versus treatment groups, based on whether they were targeted by the policy. We also used the time difference: before and after the policy change. With these two dimensions, we formed four groups: (1) Other time of the year (Control Group) - Before Domestic Movie Protection Month Policy; (2) Summer: July and August (Treatment Group) - Before Domestic Movie Protection Month Policy; (3) Other time of the year (Control Group) - After Domestic Movie Protection Month Policy; (4) Summer: July and August (Treatment Group) - After Domestic Movie Protection Month Policy. By comparing the outcome variables in each of the four groups, we were able to estimate the true effects of the policy. The regression model is as follows.

$$Y_{i,t} = \beta_0 + \beta_1 Treated_{i,t} + \beta_2 After_{i,t} + \alpha_1 Treated_{i,t} \times After_{i,t} + \epsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ is either the NLP index or the Douban Rating of movie i shown in year t, $Treated_{i,t}$ is a dummy variable which equals 1 if the movie is shown during the summer, and $After_{i,t}$ is a dummy variable which equals 1 if the movie is shown after 2014. α_1 is the coefficient of interest.

T-Test was also used to examine the effects of Domestic Movie Protection Month, and both 90% and 95% significant level were accepted. We compared between the same groups in the setting of the DID.

6. Empirical Results

6.1 Demonstration of the policy

Because the policy is never publicly announced, using the movie release information to indicate when the policy is implemented is necessary. As Figure 3 shows, the number of foreign movies shown during July and August is significantly (p-value = 7.117e-05) smaller than domestic movies than that of during the other time of the year. In Figure 4, the delay of foreign movies is also significantly (p-value = 2.2e-16) higher during July and August than during other time of the year. By comparing the foreign and domestic releasing time, we could find the delay in releasing the foreign movie. The industrial protection policy is significantly (p-value = 0.02281) more serious (as the delay of foreign movies during the summer indicated) after 2014, showing in Figure 5. The results demonstrated in Figure 2 & 3 indicates that the difference in the number of foreign and domestic movies and the delay in the domestic release of foreign movies are both substantially significant during the summer, meaning that the policy would actually be implemented during the summer. Also, Figure 4 shows that the delay in the summer significantly increase after 2014, indicating that the policy change would actually happen around 2014. With all of the data, therefore, we found that the Domestic Movie Protection Month is indeed implemented during every summer after 2014.

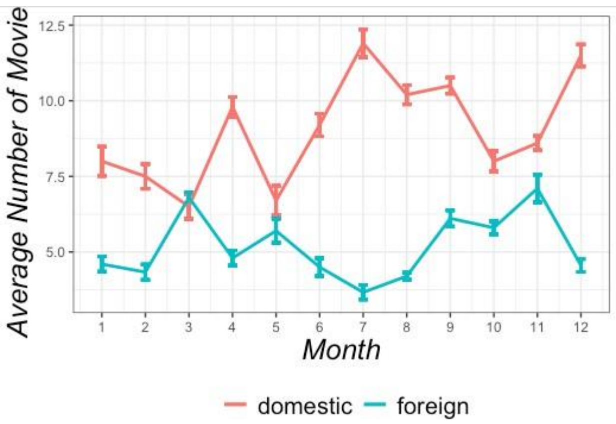

Fig. 2 A comparison of the average number of foreign and domestic movies shown in each month from 2009 to 2018. The green line represents the average number of foreign movies shown in the domestic market, and the red line represents the average number of domestic movies shown. Error bars display 95% confidence intervals.

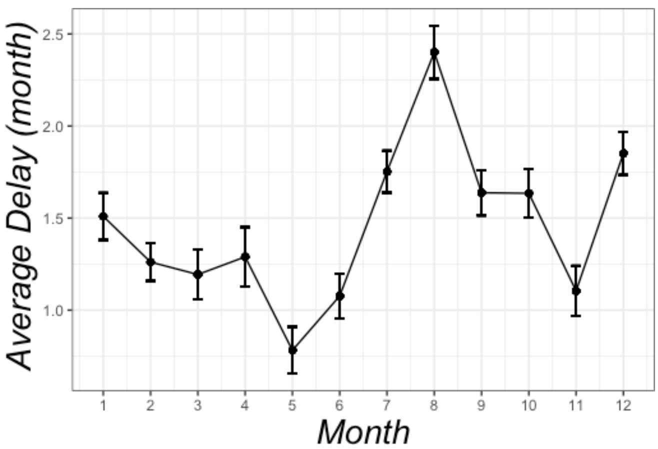

Fig. 3 A comparison of the average delay of foreign release movie in each month from 2009 to 2018. The average delay is significantly higher in July and August than the rest of the year. Error bars display 95% confidence intervals.

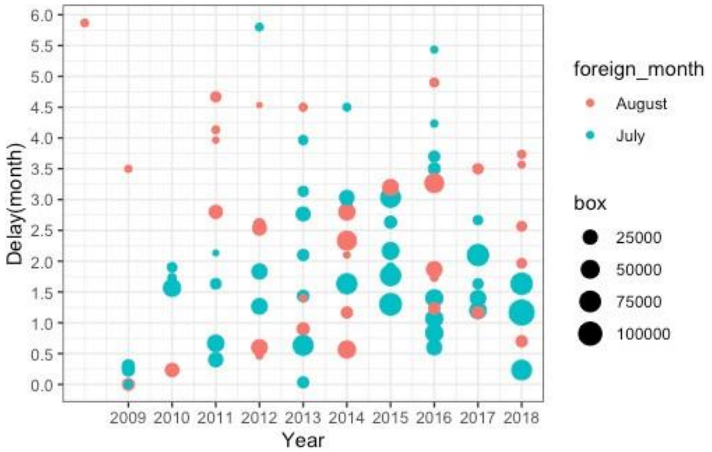

Fig. 4 Delay (in month) of each foreign movie shown in the domestic market in July and August from 2009 to 2018. Each point represents a movie.

6.2 Effects of Protection Policy

According to the data presented in Figure 5, the Douban Rating of domestic movies released during the summer was significantly higher after 2014. Figure 6 shows that the Welfare Index of domestic movies released during the summer was also significantly higher after 2014. Both Douban Rating and Welfare Index domestic movies released at other times of the year (control group), which were not affected by the industrial protection policy, remained steady/did not change significantly. Therefore, both results support Mechanism A: industrial protection policy helped domestic firms increase the incentive for quality upgrading. To corroborate the finding by the Difference-in-Difference models, we also conduct T-Tests, as the Table 5 & 6 show. Our Null Hypothesis 1 states that the Douban Rating of the domestic movies in summer time before and after 2014 is not different; in contrast, Alternative Hypothesis 1 states the Douban Rating of the domestic movies in summer time before is greater than the Douban Rating after 2014. Because the p-value (0.03826) is less than 0.05, Null Hypothesis 1 is rejected. Therefore, the Douban Rating of the domestic movies in summer time before is significantly greater than the Douban Rating after 2014. For the Welfare Index, we also set the Null Hypothesis 2, which states that the Welfare Index of the domestic movies in summer time before and after 2014 is not different. Because the p-value (0.09569) is less than 0.10, Null Hypothesis 2 is rejected. Therefore, the Welfare Index of the domestic movies in summer time before is greater than the Welfare Index after 2014. Similarly, both Douban Rating and Welfare Index of the movies shown during the summer and other times before 2014 are not significantly different. This indicates that there are no pre-trend effects.

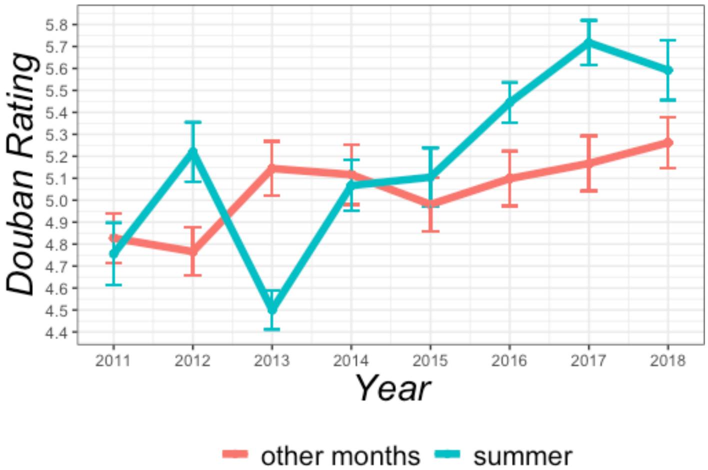

Fig. 5 Average Douban rating of domestic movies in summer (July and August) vs. other time in the year from 2011 to 2018. Green line shows the Douban rating of movies presented in the summer and red line shows the Douban rating of movies presented in the other months of the year. Error bars display 95% confidence interval.

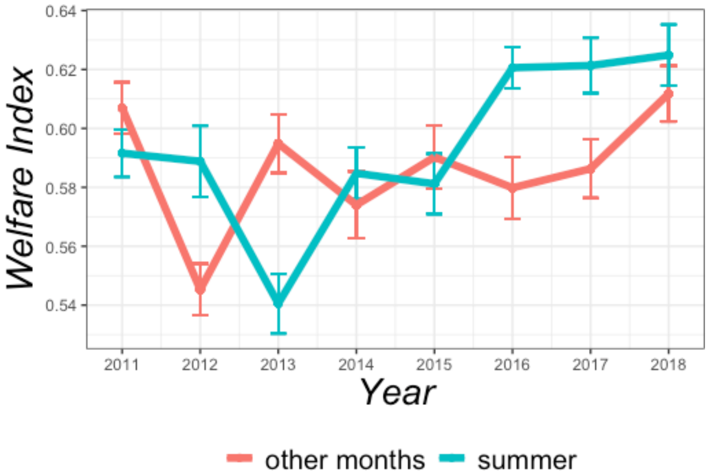

Fig. 6 Average NLP Index of domestic movies in summer (July and August) vs. other time in the year from 2011 to 2018. Green line shows the Welfare Index of movies presented in the summer and red line shows the Welfare Index of movies presented in the other months of the year. Error bars display 95% confidence interval.

Table 5. A display of the p-values resulting from the t-test between the Douban Rating of summer and other time before or after 2014.

T-TEST	P-Value	α = 0.05	α = 0.10
summer before 2014 & after 2014	0.03826	Yes	Yes
summer & other time before 2014	0.6344	No	No
other time before 2014 & after 2014	0.2215	No	No
summer & other time after 2014	0.07754	No	Yes

Table 6. A display of the p-values resulting from the t-test between the Welfare Index of summer and other time before or after 2014.

T-TEST	P-Value	α = 0.05	α = 0.10
summer before 2014 & after 2014	0.09569	No	Yes
summer & other time before 2014	0.5182	No	No
other time before 2014 & after 2014	0.1327	No	No
summer & other time after 2014	0.1976	No	No

Also, both Douban Rating and Welfare Index of the movies shown in other times before 2014 and after 2014 are also not significantly different, which suggests there is no selection issues/Zero-Sum bias. A Zero- Sum bias in this situation would lead all of the higher quality movie into the summer time, which would reduce the average movie quality of the movie's release in the other time of the year (control group). Because the T-Test shows that the movie quality in control group did not decrease over the years, the possibility of the Zero-Sum bias could be eliminated. Lastly and surprisingly, the Welfare Index of summer and other times after 2014 are not significantly different. This indicates that there might be a spillover effect, where the extra profits gained from the movies released in the summer because of the policy could be used in the investment in movie in the other time of year. Although we found a possibility of the spillover effect, we cannot draw the conclusion that there must be such an effect in Chinese Movie Industry, and further research is needed to prove the existence of the spillover effect.

7. Conclusion

This project analyzed the effect of industrial protection policy on consumer welfare. Though previous literature provided mixed results on the net effects of industrial policy, I found evidence that supports Mechanism A of the hypothesis: with the industrial protection policy, domestic firms are provided with more opportunities to grow and given more incentives to invest in quality upgrading; with the qualities of movies shown in other months being stable, the increase of movie quality during the summer after the industrial policy indicates the increase of consumer welfare in general. In the first part (from Figure 3 to 5), I showed the intensity of the industrial protection policies across years based on the number of foreign versus domestic movies shown in different months and the delay of foreign movies. This verified that the policy mainly started during summers after 2014. I then used the years before 2014 to deal with the pre-trend bias, and the years after 2014 to measure the policy impact. In the second part (Figure 6 & 7 and Table 5 & 6), I used both Douban Rating and the Welfare Index as the proxies for movie quality and consumer welfare. I found that the two proxies were both significantly higher during summers after 2014, when the domestic movie protection month policy is implemented. Before 2014, both proxies in the summer and the other time were not significantly different, suggesting that there are no pre-trend effects, where the difference between the groups already existed. The proxies of movies shown in other months were used as the control group, which are found to remain stable before and after 2014, showing there is no selection issues/Zero-Sum bias, which moves most high-quality movies to summer for reduced competition. However, only the result of the Welfare Index suggested the possible spillover effects, where the profits earned from movies in summer could be also invested in the quality upgrading of movies at the other times of the year. Thus, the patterns shown in both Douban Rating and NLP Index support Mechanism A of the hypothesis. The two proxies also provide a robustness check for each other, making the conclusion more convincing and harder to be manipulated.

8. Discussion

8.1 Future Work

In this project, I used both 95% and 90% significance levels because currently I only collected the top 40 comments of each movie for NLP analysis to produce the Welfare Index. Therefore, the welfare index from the NLP sentiment analysis can be relatively noisy. This happened because the hardware I used this time was a Mac-book that does not have a good GPU for data processing in python. With better hardware to collect more data in the future, therefore, I hope to construct a more precise index and use only a 95% significance level to provide a more robust conclusion. In addition, I can collect data from other platforms like Maoyan and Bilibili, two other movie rating websites, to enrich my data sets and provide a more comprehensive conclusion, although Douban is often considered as the most authentic movie review platform. In the future, I also aim to investigate the possible existence of the spillover effect, where the profits earned from movies in summer might be also invested in the movies at the other time of the year.

8.2 Application

Because the result shows that industry protection policies are beneficial, it provides support for policymakers on the implementation of industry protection policies in the movie industry for the future and even in other broader contexts. However, we also have to interpret the results with caution. There might be other unseen or long-run effects which needs further studies in this important field. Using NLP and more computational methods to identify consumer welfare and conduct sentiment analysis can be a growing field in the future, especially considering the massive data sets and information available on various Internet platforms. Also, consumer welfare provides another important dimension to examine the effects of the industrial policies, in addition to the regular available information such as box offices.

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