Globalization and the Rise of Action Movies in Hollywood

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Abstract

This paper shows that Globalization contributes significantly to the rise of Action movies in Hollywood. Incorporating both the intensive and extensive margins in trade, this paper develops a structural model to allow movie-quality production heterogeneity across genres and countries. The paper finds that Hollywood studios respond to export-market expansion by tailoring their products to international consumers' preferences. As a result, Hollywood increasingly focuses on a few blockbusters, overwhelmingly in the Action genre. The movie industry becomes significantly more concentrated both domestically and abroad. Furthermore, a disproportionate increase in Action movies raises consumer welfare in some countries at other regions' expense.

Keywords: Globalization, Movies, Budget Reallocation, Quality Heterogeneity.

1 Introduction

In the past twenty-five years, the movie industry in Hollywood has experienced two tectonic shifts.[1] First, movies of the Action genre have become dominant at the box-office.[2] Their aggregate domestic market share has increased by almost 20 percent and accounts for more than half of the total box-office revenue in the US. Second, Hollywood has become increasingly reliant on foreign markets. The US share of the worldwide box-office revenue has declined from almost 60 percent in the mid-1990s to less than 40 percent in 2016.

To explain these two parallel developments in the movie industry, this paper asks two important questions. First, how does Globalization contribute to the rise of Action movies in Hollywood? Second, how does the rise of Action movies impact consumer welfare worldwide? Answers to these questions are not only important to the movie industry, but also have wide implications in consumer-goods industries and international trade in general.

Previous studies of Globalization have primarily focused on the impact of widening international markets and lowering trade barriers on the efficiency of resource allocation *across firms*. In his seminal work, Melitz (2003) has established that trade can lead to intra-industry resource reallocation from firms of low productivity to those of high productivity. Our research builds on the previous work and sheds lights on the efficiency of resource allocation *across different types of goods*. This paper recognizes that consumer preferences vary across nations. As the international market becomes more important, domestic producers reallocate resources to product types that suit the international consumers' preferences. As a key contribution, our paper shows that Globalization can select products by their inherent characteristics and affinities to consumer tastes.

To understand Globalization's contribution to the rise of Hollywood Action movies, this paper considers both the extensive and intensive margins. On the extensive margin, this paper builds on the international trade literature (e.g. Melitz (2003)). In the movie industry, Action movies, on average, have higher perceived qualities and enjoy wider export opportunities. Therefore, Globalization and the expansion of international markets can dis-

[1]In the paper, we use the term "Hollywood movies" to refer to US-produced movies or movies of US-origin.

[2]In the paper, the "Action" genre includes movies classified as either action or adventure films, as these genres have significant overlaps.

proportionately enlarge the Action movies' market size and further their advantage over Non-Action movies.

On the intensive margin, consumers in foreign export markets, relative to US domestic audiences, have a stronger preference for Hollywood Action movies over those Non-Action ones. Intuitively, Action movies face fewer cultural and language barriers. Compared to the US counterpart, the international consumer demand may respond more to an investment increase in Action movies than in Non-Action movies. Therefore, on the intensive margin, as the international market becomes more important, Hollywood studios reallocate budget investments from Non-Action to Action movies to satisfy the international audiences. Interestingly, trade may *not* be universally beneficial to consumers everywhere, as a disproportionate increase in one type of product can raise consumer welfare in some countries at other regions' expense.

Incorporating both margins, this paper develops a structural model of movie industry demand and supply and characterizes the industry outcome using a Nash Equilibrium. In the model, movie producers make both production budget and export decisions to maximize profits. For consumers, a movie's perceived quality depends on its genre and production budget.[3] A movie's genre, determined by its screenplay and conception, is exogenous throughout its production and consumption. However, producers can endogenously improve a movie's quality by raising its production budget.

Furthermore, the model allows for a movie's quality to respond to its budget investment heterogeneously across countries. Movie qualities are inherently subjective to consumer preferences and vary across countries and cultures. For example, *12 Years a Slave*, a biographical period drama set in the US Antebellum South, won the Academy Award for Best Picture but had hardly any presence in East Asian countries. In contrast, *Iron Man 3*, a super-hero action movie released in the same year, was more popular overseas, and its gross box-office revenue in the international markets was twice as much as that in the US. Hence, the same budget investment in a movie can result in different quality improvements in different countries. As a result, the model allows budget elasticity of perceived quality by genre to differ

[3] A movie's quality refers to consumer perceived quality, which is revealed by a movie's box-office revenue. It reflects, but it is *not* the same as, artistic quality or critical responses.

across regions in the world.

The structural model is estimated using a Simulated Method of Moments procedure. We match the simulated model moments with their empirical targets, including aggregate box-office revenues, market shares, and export probabilities by movie genre and budget level across different countries. We generate the empirical moments from a dataset of all US-origin movies released between 2007 and 2016 in 44 countries. The estimated model fits well the targeted moments and the movie size distributions in both the US domestic and the international export markets.

To quantify the impacts of Globalization on the movie industry, we conduct counterfactual policy experiments focusing on one particular country - China. The tremendous economic growth and trade liberalization in the past three decades has turned China from a non-importer to the second-largest consumer market of Hollywood movies in the world.

We draw four conclusions from the counterfactual experiments. First, the emergence of the Chinese market has a significant impact on the rise of Action movies in Hollywood. A simulated increase of Chinese market size from zero to its current size leads to a disproportionate increase in Action movies' production budgets and export probabilities. The aggregate market shares of Action movies in the US domestic and foreign export markets would increase by 16.4 and 18.2 percentage points, respectively. The movie industry becomes significantly more concentrated. Hollywood movie producers increasingly focus on a few blockbuster movies, overwhelmingly of the Action genre.

Second, we investigate the relative importance of the extensive and intensive margins in the global movie trade. The extensive margin turns out to matter little in the rise of Action movies. In the counterfactual experiments, whether allowing every movie equal access to enter China or imposing stricter import quotas in the Chinese market, the Action movies' aggregate rising pattern remains mostly unchanged.

Third, we quantify the importance of movie quality production heterogeneity across countries. In a counterfactual world where the budget elasticities in China are the same as those in the US, the rise in Action movies would virtually disappear. Overall, the difference in budget elasticities across regions can explain up to 93.3 percent and 80.7 percent of the Action movie market share increases in the US and the international markets, respectively.

Lastly, the rise of Action movies has different impacts on consumer welfare across countries. Action movies' disproportionate rise significantly benefits international consumers, especially in Asia, where Non-Action movies are the least likely exported. However, controlling for aggregate industry budget increase, we find that a relatively higher market share of Action movies can potentially cause consumer welfare losses in regions with significant consumption of Non-Action movies, such as the US market. Our results illustrate a potential downside of Globalization. While producers increasingly tailor their products to attract international consumers, domestic consumers can be worse off.

2 Literature Review

Previous literature on the movie industry has largely focused on understanding the determinants of movie box-office performances.[4] Ainslie, Dreze, and Zufryden (2005) and Einav (2007) are among the first to develop a discrete-choice model of movie demand, which is a critical determining factor of movie performance. Einav (2007) focuses on the movie industry's underlying seasonality and studies the market expansion effects. Building on Einav (2007)'s structural demand framework, subsequent papers contribute to a richer understanding of consumer behaviors and producer supply decisions in the movie industry. For example, Moul (2007) studies the word-of-mouth effect on consumer expectations of movies.

Building on the established movie demand framework, our paper contributes to understanding strategic considerations in the movie production and distribution process. In the literature, several papers study the early stage of movie production. Luo (2014) finds that, in the market for original movie ideas, buyers are reluctant to meet unproven sellers for early-stage ideas, which restricts sellers to either developing the ideas fully (to sell them later) or abandoning them. Some studies investigate the sequential market entry of movies in different channels. Prasad, Bronnenberg, and Mahajan (2004) and Hennig-Thurau, Henning, Sattler, Eggers, and Houston (2007) analyze the optimal sequential timing policy between theatrical release and DVD release; Holloway (2017) studies how distributors learn about their

[4] See De Vany and Walls (1996), De Vany and Walls (1999, 2004), Filson, Switzer, and Besocke (2005), Hennig-Thurau, Houston, and Walsh (2006), Walls (2009), and Filson and Havlicek (2018).

movie's quality with sequential market entry. While not explicitly modeling the production origination process or the strategic game in release timing, our paper provides insights on Hollywood studios' strategic investment choices in response to changes in market conditions.

Our paper also contributes to the trade literature, in particular, on the international trade of cultural goods. Most of the trade literature, following Melitz (2003), have shown that trade liberalization can enhance industry productivity and improve consumer welfare. On the trade of cultural goods, however, Francois and van Ypersele (2002) have shown theoretically that restrictions on trade can be welfare improving. Our paper shows that intra-industry resource reallocation across different types of products can benefit consumers in one region of the world at the expense of consumers in another region.

One motivating factor for allowing budget elasticity heterogeneity in our paper is that countries are culturally distinctive. Hermosilla, Gutierrez-Navratil, and Prieto-Rodriguez (2018) show that Chinese society has an aesthetic preference for lighter skin, and provide evidence that this can be linked to the more frequent casting of pale-skinned stars in Hollywood films targeting the Chinese market. We can also trace the intuition to empirical works, such as Marvasti and Canterbery (2005) and Hanson and Xiang (2008), which measure trade costs of cultural goods based on cultural distance. Our structural model allows for endogenous entry into foreign markets. In particular, all movies face the same destination-specific export costs, which are identified using variations in observed movies' export decisions. Our approach is largely consistent with the literature, such as Hanson and Xiang (2011), which uses versions of the Melitz (2003) model to estimate the global fixed export costs of movie trades.

In the literature, Ferreira, Petrin, and Waldfogel (2016) is the closest to our paper. The demand models in both papers are variants of the Einav (2007) structural demand framework. Also, we use a similar equilibrium concept and focus on the same country - China. However, this paper is distinct from Ferreira, Petrin, and Waldfogel (2016) in three significant ways.

On the structural model front, we differentiate ourselves by explicitly modeling producer export decisions *in addition* to their budget decisions. Directly modeling export decisions allow us to evaluate the importance of the extensive margin relative to the intensive margin. It further enables us to directly assess the impacts of trade restrictions, such as the movie import quotas in China. In addition, we show that export decisions contain vital information for identifying a movie's quality production function in a given country. This information is especially relevant when a movie is not exported to the country, so its box-office performance in that country cannot be directly observed.

Furthermore, our model incorporates heterogeneities in movie quality production by genre across different countries. In particular, movies of different genres can have different budget elasticities of perceived quality within a country. Our empirical estimation suggests that this extra model flexibility is necessary to fit important industry moments, such as within-industry market shares and export probabilities. Our counterfactual experiments also show that the regional heterogeneity in budget elasticities by genre is the main driving force behind the rise of Action movies in Hollywood.

Last but not least, our research focus is different from that of Ferreira, Petrin, and Waldfogel (2016). While they focus on the impact of consumer preference externalities on global trade patterns, we are primarily interested in how producers re-allocate resources across different types of products. Similar to Ferreira, Petrin, and Waldfogel (2016), we find that trade liberalization can cause an aggregate increase in investments in Hollywood movies, which by itself can be beneficial to consumers everywhere in the world. On top of that, our paper quantifies welfare changes due to resource reallocation within the industry. Based on our estimates, with the Chinese market's expansion, only one-third of the international consumer surplus increase comes from the aggregate budget increase, and two-thirds of the increase comes from a resource reallocation to Action movies. In the US domestic market, our counterfactual results suggest that the inter-genre resource reallocation causes a loss in consumer surplus, which partially offsets the gains due to increased aggregate budget investments.

3 Data and Industry Background

This section details the data sources and describes the procedure of constructing and combining the data used in model estimation. This section also provides the industry backgrounds and evidence to motivate our empirical model.

3.1 Data Summary

The movie box-office revenue data are from two widely used online movie data providers, *The Numbers* and *Box-office Mojo*.[5] *The Numbers* provides detailed annual movie box-office data in the US, as well as information on release dates, number of theaters, production budget estimates, and genres. The *Box-office Mojo* provides annual box-office data for all the international markets used in this paper. In addition to the US market, we use data from 43 countries in four main regions - Asia, Eastern Europe, Western Europe, and South America. Countries are grouped into their respective regions based on both geo-political boundaries and cultural closeness. We use the some regional memberships as in the "Regional Groups of Member States" of the United Nations.[6] The countries and their corresponding regions are listed in Table A1 of the Appendix.

The combined data covers all movies released in these 44 countries between January 1, 2007, to December 31, 2017.[7] The main sample comprises 24,471 movie titles, of which many non-US produced movies were only released in their home countries. Our analysis focuses on Hollywood movies (i.e., movies of US-origin) in wide-release.[8] Of these movies, we observe production budgets of 1,411 US-origin wide-release movies.[9] Our final data contains 100,496 movie-country-year observations.

In a given country, a movie's market share is its box-office revenue in that country divided by the country's overall market size. A country's market size is its movie-going population size multiplied by the country's average movie ticket price. When calculating the size of a potential movie-going population, we assume that an individual consumer goes to theaters at most one time per month. Therefore, a country's movie-going population

[5]Their URLs are `https://www.the-numbers.com/` and `https://www.boxofficemojo.com/`, respectively.

[6]The "Regional Groups of Member States" are from the U.N. website, `https://www.un.org/depts/DGACM/RegionalGroups.shtml`.

[7]Some countries do not have data available in the entire period. For example, the *Box-office Mojo* only provides data for the Chinese market in 2007, 2008, and 2013-2017. In the counterfactual simulations, we used the data of 2013-2017 as the baseline for comparison.

[8]Based on Industry definition, wide-releases refer to those movies released to at least 600 theaters in the American market.

[9]The data has budget estimates of more than 90 percent of the US-origin movies. All the US-origin movies are used in the demand estimation. However, the supply-side estimation use only those movies with budget information.

size is twelve times the country's actual population. The US annual average ticket prices are from the *Encyclopedia of Exhibition*, published by the National Association of Theater Owners. The average ticket prices of all other countries are obtained from the *UIS.Stat*, the official statistical database compiled by UNESCO.[10] UNESCO's movie ticket price data are available from 2005 to 2015. We use linear interpolation to obtain average prices for the missing years in our data. The population sizes and national incomes per capita of all countries are from the World Bank.

Table 1: Summary Statistics of Main Variables

	Asia	E. Europe	S. America	US	W. Europe
Income ($1,000)	23.23	12.79	9.78	52.35	49.28
	(17.60)	(6.28)	(3.11)	(3.38)	(14.32)
Ticket Price ($)	6.45	5.21	4.43	7.95	10.13
	(3.29)	(1.80)	(1.44)	(0.58)	(2.19)
Population (million)	173.30	30.07	64.21	313.80	29.21
	(379.10)	(39.65)	(64.12)	(7.92)	(27.37)
Movie's Market Share (%)	0.07	0.04	0.06	0.22	0.08
	(0.05)	(0.02)	(0.09)	(0.02)	(0.06)

Notes: The table shows mean values of main variables across regions used in the analysis. Standard deviations are in parenthesis.

Table 1 reports the summary statistics of regional income, ticket price, population size, and movie market share. As expected, the US and Western European countries have the highest incomes and ticket prices. The average population per country is the highest in the US and Asia. A movie's average market shares vary significantly across regions. The US has the highest average market share of 0.22 percent, while Eastern Europe has the lowest average market share of 0.04 percent.

The data categorizes movies based on their genres and production budgets. Based on the genre definitions from *The Numbers*, we group movies into two broad genre categories - Action and Non-Action movies. Action movies include "action" films, such as "the Avengers," and "adventure" films, such as the "Harry Potter" movies. All other films are considered Non-Action movies, including drama, comedy, horror, and musical films. We further group

[10]UNESCO collects data and constructs internationally-comparable data on culture products, such as movies, see http://data.uis.unesco.org.

movies into two categories based on their production budgets, which serve as a crude proxy for the unobservable movie qualities.

Hence, the data has four movie categories, namely, "Low-Budget Action," "High-Budget Action," "Low-Budget Non-Action," and "High-Budget Non-Action." For example, a "Low-Budget Action" movie is an Action movie with its production budget below the *median* of all Action movies released in the same year. By regions and movie categories, Table 2 summarizes the average budgets, export probabilities and market shares.

Table 2: Average Export Probabilities and Market Shares

	Non-Action		Action	
	Low-Budget	High-Budget	Low-Budget	High-Budget
Average Production Budget, in Millions of Dollars				
Budget	15.03	56.75	60.22	171.30
Export Probabilities				
Asia	40.85%	57.92%	70.64%	85.78%
E. Europe	45.36%	72.66%	75.90%	90.41%
W. Europe	61.91%	83.51%	82.40%	94.94%
S. America	57.22%	78.20%	80.22%	89.71%
US	100.00%	100.00%	100.00%	100.00%
Market Shares				
Asia	0.03%	0.08%	0.10%	0.32%
E. Europe	0.02%	0.06%	0.06%	0.13%
W. Europe	0.06%	0.14%	0.12%	0.34%
S. America	0.03%	0.08%	0.10%	0.25%
US	0.13%	0.26%	0.22%	0.65%

Notes: The table shows average production budgets, export probabilities and market shares (conditional on entry) by movie category across regions.

The upper panel of Table 2 shows the four movie categories' average production budgets. Action movies, on average, have higher budgets than Non-Action movies. Interestingly, Table 2 shows that even the Low-Budget Action movies have a higher average budget than the High-Budget Non-Action movies. The cross-genre budget difference indicates that the production of Action movies can be very different from Non-Action movies. In recent years, Action movies typically spend a significant fraction of their budgets on expensive special effects using Computer Generated Imagery (CGI). For example, the Marvel Studio's "The Avengers", released in 2012, had a budget of \$220 million, of which more than half (approximately \$120 million) were on the special effects.

The middle panel of Table 2 reports Hollywood movies' export probabilities in different regions. Because we only consider US-origin movies, all movies have a 100 percent probability of entering the US market. In all other regions, Action movies and high-budget movies are more likely to be exported. Movies' export decisions are clearly correlated with their budgets and genres. For each movie category, Western Europe is the most likely export destination, and Asia is the least likely. The export probability difference across regions suggests that movies may face different entry costs in different export destinations.

The lower panel of Table 2 reports Hollywood movies' market shares conditional on entry. Within a genre, movie market shares are positively correlated with budgets. High-Budget movies' average market share can be two to three times higher than Low-Budget ones in a given region. Across regions, the relative market shares between Action and Non-Action movies can vary significantly. For example, the average market share of High-Budget movies is 2.6 times that of Non-Action movies in the US. Western Europe and Eastern Europe have similar ratios of average market shares by genre, which are 2.7 and 2.2, respectively. In contrast, Asia and South America have markedly higher ratios of 3.2 and 3.1, respectively. Evidently, the lower panel of Table 2 shows the cross-region differences in relative popularity (or perceived quality) between genres.

Overall, Table 2 summarizes the important empirical moments used to estimate our structural model. Later on, we will discuss how the variations in these moments across movie categories and regions help identify important model parameters.

3.2 Industry Background

In the past two decades, Action movies have experienced a steady rise in Hollywood. From 1995 to the present, Action movies' market share of the domestic box-office revenue has risen from 35.7 percent to 53.0 percent.[11]

Meanwhile, the US movie industry has seen a reallocation of production budget across genres. In 1995, Action movies' aggregate production budget was 53.5 percent of Hollywood's

[11] The number of Action movies has modestly increased. Approximately 20 percent of all annual releases were Action movies before 2000, and this figure has risen to about 25 percent in recent years.

total budget investment. Action movies' budget share has since risen to 62.1 percent. Besides, Action movies have experienced an increase in box-office revenues. Compared to the mid-1990s, the average domestic box-office of an Action movie in recent years has increased by $40.4 million (2019 dollars, adjusting for inflation), while an average Non-Action movie has lost $9.7 million in box-office revenue.

In recent years, almost all the top-ten movies in the US box office are Action movies, while blockbusters in other genres are becoming exceedingly rare. The industry has fundamentally changed since the 1990s when blockbuster dramas like "Forrest Gump" can reign supreme at the box office.

A parallel development during the same period was the increasing exposure to international movie markets due to Globalization. As several emerging economies grew in market size, their demand for Hollywood movies correspondingly increased. From 1995 to the present, the international markets' share of total Hollywood movie box-office revenues has increased from approximately 40 percent to 60 percent.

China is a prime example of these emerging economies. In the past twenty-five years, the Chinese economy has experienced tremendous growth, fueling an exponential increase in Chinese movie consumption. From 2009 to 2019, the number of Chinese cinema screens has grown from 4,723 to 69,787, an almost fifteen-fold growth.[12] With such an explosive increase in demand, the Chinese market has become a dominant force in the movie industry.

Hollywood movies started to enter China officially in the mid-1990s. In November 1994, "The Fugitive," starring Harrison Ford, was the first to be released in China. In 1995, six US movies were released China.[13] While the Action movie "True Lies" was the most successful Hollywood film in China that year, the Oscar-winning drama "Forest Gump" was a relative failure.[14] Even for "True Lies," the gross Chinese box office revenue of $12.3 million was inconsequential, compared to the US box-office gross of $146.3 million, and the total worldwide gross of $365.8 million. By the mid-2010s, China has become the second-largest market for Hollywood movies. At least 10 percent of Hollywood's annual gross box-office

[12] The Chinese cinema screen data is from https://www.statista.com/statistics/279111/number-of-cinema-screens-in-china/.

[13] These movies were previously released in the US in 1994.

[14] For more details, see the report *Hollywood's crusade in China prior to China's WTO accession*, http://www.ejumpcut.org/archive/jc49.2007/TingWang/2.html.

revenue now comes from China. China has become a prime export destination, especially for blockbuster Action movies. For "Avengers: Infinity War" released in 2018, the Chinese box-office revenue was $360 million, which was more than half of the North American revenue.

Hollywood movies also face various trade restrictions in the Chinese movie market. Foreign movies can enter China in three ways.[15] First, the state-owned China Film Group Corporation (CFGC) imports 20-30 movies per year on a flat-fee basis. With a limited budget, the CFGC typically only distributes those "outdated and low-grade but cheap" movies.

Second, Hollywood movies can enter the Chinese market using a revenue-sharing contract. The China Film Administration imposes an annual import quota on foreign films under these revenue-sharing contracts. Before China's WTO accession in 2001, the import quota was only ten movies per year. In 2007, China was found in violation of the WTO rules. By 2012, China had agreed to increase the quota from 20 to 34 foreign movies per year.

The third channel of entering the Chinese market is through co-production. An agreement between China and the US in 2012 has set concrete guidelines for movie co-production. According to the agreement, foreign producers may obtain attractive revenue sharing terms if they collaborate with Chinese investors and their movies feature Chinese actors, settings, and themes. These co-produced movies are not subject to the import quota. Movie co-production agreements are subject to the approval of the Chinese National Radio and Television Administration (formerly the State Administration of Radio, Film, and Television).

Beyond trade restrictions, Hollywood movies face significant cultural and language barriers to enter China and other emerging economies. Both geographic and cultural distances can potentially affect the trade pattern in the movie industry, as pointed out in the previous literature (Marvasti and Canterbery (2005); Hanson and Xiang (2008)).

4 Model

In this section, we develop an equilibrium model of the global movie industry. The demand side consists of a nested logit discrete choice model. On the supply side, producers make endogenous movie budget and export decisions. The model timing is static, and every movie

[15] For more details, see Ho, Rysman, and Wang (2019).

is in theaters for only one period.

4.1 Demand

Following Einav (2007) and the movie demand literature, we use a nested logit discrete choice model. Because the model is static, the time subscript t is suppressed in the following exposition to simplify model notation.

Consumers make two sets of nested choices every period. A consumer first chooses whether to watch a movie in theaters. If yes, then the consumer decides on which movie to watch. The indirect utility of consumer i in country c watching movie j is

$$u_{ijc} = \beta_0 + \alpha p_c + \phi y_c + \xi_{jc} + \zeta_{ic} + (1-\sigma)\varepsilon_{ijc} = \theta_{jc} + \zeta_{ic} + (1-\sigma)\varepsilon_{ijc}, \quad (1)$$

where p_c is the movie ticket price in country c, and y_c is the per capita income of country c. Parameters α and ϕ correspond to marginal utilities of price and income, respectively. Parameter β_0 is the average utility of going to theaters, which is assumed to be the same across all countries. The demand shock, ξ_{jc}, captures consumers' unobserved propensity to like a movie in country c. We define movie j's perceived quality in country c as $\theta_{jc} = \beta_0 + \alpha p_c + \phi y_c + \xi_{jc}$.

A consumer can stay away from movie theaters and consume an outside option, which is always available. Consumer i's utility of choosing the outside option "0" in country c is

$$u_{i0c} = \zeta'_{ic} + (1-\sigma)\varepsilon_{i0c}, \quad (2)$$

The nested logit demand has two idiosyncratic taste shock components, ζ_{ic} and ε_{ijc}. The component, ε_{ijc}, is an extreme-value distributed random variable, which is independently and identically distributed (i.i.d.) across consumers, movies, and countries. The component, ζ_{ic}, is the unobserved propensity to go to movie theaters, which is the same across all movies. However, ζ_{ic} can be different from ζ'_{ic} – the unobserved propensity to choose the outside option. The sum, $\zeta_{ic} + (1-\sigma)\varepsilon_{ijc}$, is also extreme value distributed. The parameter $\sigma \in [0, 1]$ captures the relative importance between these two taste shocks and measures the substitutability between going to theaters and the outside option.

Following Berry (1994), the market share of movie j in country c is:

$$s_{jc} = \frac{\exp\left(\frac{\theta_{jc}}{1-\sigma}\right)}{D_c^{\sigma} + D_c}, \quad \text{where:} \quad D_c = \sum_{k \in J_c} \exp\left(\frac{\theta_{kc}}{1-\sigma}\right). \tag{3}$$

Here, J_c is the set of all available movies in country c for a given period. We can similarly define the outside option's market share in country c to be s_{0c}. Rearranging Equation (3) results in the following demand equation:

$$\ln(s_{jc}) - \ln(s_{0c}) = \beta_0 + \alpha p_c + \phi y_c + \sigma \ln\left(\frac{s_{jc}}{1 - s_{0c}}\right) + \xi_{jc}. \tag{4}$$

The parameter σ captures the "market-expansion" effect. If $\sigma = 1$, then all movies-in-theater have no substitutability with the outside option, in which case a movie can only expand its market share at other movies' expense. If $\sigma = 0$, then the model is a simple logit model, in which case the cross-elasticity of demand is the same across all movies and the outside option. The magnitude of σ determines the relative size of the market-expansion effect.

In Equation (4), both the within-market share $\ln\left(\frac{s_{jc}}{1-s_{0c}}\right)$ and the price p_c can be potentially endogenous. The unobserved propensity to like movie j in country c can be thought as having two components, $\xi_{jc} = \omega_{jc} + \varsigma_{jc}$, where ς_{jc} is an i.i.d. measurement error, and ω_{jc} is an unobserved demand shock that varies across movies in country c. We use an instrumental variable approach to correct the endogeneity bias in the demand estimation. We will discuss the choice of instrumental variables in Section 6.1.

4.2 Supply

On the supply side, movie producers make two decisions for each movie. First, they decide on a movie's production budget to improve the movie's quality. Then, they decide on the export destinations. This subsection specifies the movie quality production function and details the producers' two-step decision-making process.

4.2.1 Movie Quality Production

When deciding on budget investments, a movie producer considers the exogenous factors such as genre, release time period, and country. The movie quality production function is

$$\delta_{jc} = \mu_c + \gamma_{1r} A_j + \gamma_{2r} \ln(B_j) + \gamma_{3r}(A_j \times \ln(B_j)) + \tau_{1r}(t - t_0) + \tau_{2r}(t - t_0)^2 + \epsilon_{jc}. \quad (5)$$

Movie j's price-adjusted quality in country c, $\delta_{jc} = \beta_0 + \phi y_c + \xi_{cj}$, can be directly recovered from the demand estimates. In Equation (5), μ_c is a country-specific fixed effect, and A_j is movie j's genre. If movie j is an Action movie, then $A_j = 1$; otherwise, $A_j = 0$. The production function is heterogeneous across five global regions: Asia, Western Europe, Eastern Europe, South America, and the US. As mentioned previously, we define these regions based on geographic and cultural closeness. Parameters γ_{1r}, γ_{2r}, and γ_{3r} are all region-specific. In particular, γ_{1r} captures the additional appeal of Action movies in region r, compared to Non-Action movies in the same region. Parameter γ_{2r} is the marginal effect of increasing budget investment on quality. Parameter γ_{3r} captures the difference in marginal effects of budget between Action and Non-Action movies. Movie j's release period is t. Given a predetermined initial period, t_0, parameters τ_{1r} and τ_{2r} capture the time trends in region r related to potential macroeconomic changes.[16]

The estimation of Equation (5) can potentially face the omitted-variable bias. For example, a potential omitted variable is the quality of movie screenplays. A higher-quality screenplay can raise both a movie's production budget and its perceived quality, thus confounding the identification of the budget investment's causal effect on quality. We use an instrumental variable approach to deal with the omitted variable bias. We will discuss the choice of instrumental variables in Section 6.2.

[16]Parallel to the movie industry Globalization, the Internet has become increasingly essential to everyday life. More people are watching movies via streaming services like Netflix and Amazon. A regional time trend can partially capture the changes in consumer movie-viewing habits and online behaviors. Enabling model identification, the time trend is assumed to be the same for all movies in the same region. Due to data limitations, we cannot capture how this parallel trend affects individual movies. Therefore, we cannot eliminate online streaming as a possible cause of the rise of Action movies. In addition, movie piracy has become more prevalent over time in many international markets (see Dalton and Leung (2017), Danaher and Waldfogel (2014) and McCalman (2005)). While we do not explicitly model movie piracy, the time trend specification can capture the increasing global prevalence of movie piracy.

The endogenous variables, the logarithm of production budgets and its interaction term with movie genre, $\ln(B_j)$ and $A_j \cdot \ln(B_j)$, are functions of the instrumental variable, z_j, and the exogenous variables,

$$\ln(B_j) = \tilde{\mu}_1 + \tilde{\tau}_{1,1}(t - t_0) + \tilde{\tau}_{2,1}(t - t_0)^2 + \tilde{\gamma}_{3,1}A_j + \tilde{\chi}_{1,1}z_j + \tilde{\chi}_{2,1}A_j z_j + \nu_{1,j}; \quad (6)$$

$$A_j \ln(B_j) = \tilde{\mu}_2 + \tilde{\tau}_{1,2}(t - t_0) + \tilde{\tau}_{2,2}(t - t_0)^2 + \tilde{\gamma}_{3,2}A_j + \tilde{\chi}_{1,2}z_j + \tilde{\chi}_{2,2}A_j z_j + \nu_{2,j}. \quad (7)$$

In Equations (6) and (7), $\tilde{\mu}_1$, $\tilde{\tau}_{1,1}$, $\tilde{\tau}_{2,1}$, $\tilde{\gamma}_{3,1}$, $\tilde{\chi}_{1,1}$, $\tilde{\chi}_{2,1}$, $\tilde{\mu}_2$, $\tilde{\tau}_{1,2}$, $\tilde{\tau}_{2,2}$, $\tilde{\gamma}_{3,2}$, $\tilde{\chi}_{1,2}$, and $\tilde{\chi}_{2,1}$ are all parameters. We regress Equations (6) and (7) to recover the residuals $\hat{\nu}_{1,j}$ and $\hat{\nu}_{2,j}$. Then, we use the estimated $\hat{\nu}_{1,j}$ and $\hat{\nu}_{2,j}$ to control for omitted variables in the quality production function estimation.

We make two crucial assumptions when applying the control function approach. First, the model abstracts away from movies' entry decisions into the US market and assumes all potential movies are released in the US. The dataset contains only wide-release movies of US-origin and has no adequate proxy measures of potential entrants who choose not to enter the US market. Additionally, many movies, not green-lit by studios for wide-release, are released in a limited number of theaters or the direct-to-consumer home video/streaming market. These movies behave very differently in the consumer market and would require a different demand specification. Furthermore, movie studios often engage in complicated entry games involving scheduling and adjusting movie release times, which is outside the scope of this paper. Second, we assume that the movie-specific omitted variables, $\nu_{1,j}$ and $\nu_{2,j}$, do not vary across different countries. If the omitted variables are related to screenplays, the unobserved screenplay qualities should remain the same in all regions.

Based on these two assumptions, we use *only* the US data to estimate Equations (6) and (7). Because we do not use data from other countries to recover the omitted variables, our approach avoids the selection bias with endogenous export decisions, which can render the instrumental variables invalid (see Ciliberto, Murry, and Tamer (2018)).

We use the same estimated residuals, $\hat{\nu}_{1,j}$ and $\hat{\nu}_{2,j}$, in the production functions of all export destinations. The movie quality production function of movie j in country c becomes

$$\begin{aligned}\delta_{jc} = \quad & \mu_c + \gamma_{1r} A_j + \gamma_{2r} \ln(B_j) + \gamma_{3r}(A_j \times \ln(B_j)) + \tau_{1r}(t - t_0) + \tau_{2r}(t - t_0)^2 \\ & + \chi_1 \cdot \hat{\nu}_{1,j} + \chi_2 \cdot \hat{\nu}_{2,j} + e_{jc}. \end{aligned} \tag{8}$$

The random shock $e_{jc} \sim N(0, \rho_c)$ is i.i.d. across movies and countries. The standard deviations of random shocks, ρ_c, can vary across countries.

The model assumes all movie producers can observe genres (A_j) and quality shocks ($\nu_{1,j}$ and $\nu_{2,j}$) of all movies released in the same period. The timing of movie producers' decisions is as follows:

1. Movie producers make simultaneous production budget decisions, after which all movie budgets (B_j) become public information;

2. Movie-country specific random demand shocks (e_{jc}) are realized;

3. Movie producers make export decisions.

Movie producers make budget decisions before export decisions. In other words, when making budget decisions, movie producers do not yet know the export destinations of their own movies or those of their competitions.

We next detail the movie producer decisions using backward induction in two stages - the export decision stage and the budget decision stage.

4.2.2 Export Decision Stage

At the beginning of the export decision stage, movie j's genre A_j, budget B_j, release period t, and all the movie-country random shocks e_{jc} are realized and are common knowledge. According to Equation (8), movie j's perceived quality in country c, δ_{jc}, also becomes known to all producers.

A producer can determine movie j's revenue in country c given all other movies' export decisions. Equation (3) gives movie j's market share in country c, s_{jc}, which is a function of δ_{jc} and perceived qualities of all other movies who choose to enter country c. Upon exporting to country c, the revenue of movie j in country c is

$$R_{jc} = W_j \cdot p_c M_c s_{jc}, \tag{9}$$

where p_c is the ticket price, and M_c is the market size of country c. Movie j's producer revenue can be different from its gross box-office revenue, $p_c M_c s_{jc}$, for two reasons. First, movie producers must share a significant portion of gross box-office revenues with movie cinemas. Second, producers have other revenue sources, such as home video, television, and on-line streaming. For this reason, the model adjusts movie j's gross box-office revenue by a movie-specific revenue weight factor, W_j. All movies face the same country-specific entry cost, F_c, which includes any country-specific distribution costs and transaction costs of adhering to local government guidelines.

Following previous works, such as Einav (2010), we assume producers make entry decisions sequentially. In each country c, movies' weighted qualities ($W_j \delta_{jc}$) determine the order of entry decisions. In a country, higher-quality movies make entry decisions first.[17]

Under the sequential entry assumption, when making entry decision into country c, movie j knows the entry decisions of all those movies with higher weighted qualities. Movie j's highest possible revenue is $\hat{R}_{jc}$, assuming all movies with lower qualities choose not to enter. Movie j decides to enter country c if $\hat{R}_{jc} \geq F_c$; and chooses not to enter if otherwise.

With sequential entry, additional entries would not alter movie j's entry decision. Additional entries must have lower weighted qualities than movie j. If a lower quality movie can enter and earn enough revenue to cover the fixed cost, then movie j must be able to so as well. Therefore, there exists a marginal movie $\bar{j}$, such that $\hat{R}_{\bar{j}c} \geq F_c$, and the next-in-line movie k has its revenue, $\hat{R}_{kc} < F_c$. In other words, all movies with weighted qualities higher or equal to $W_{\bar{j}} \cdot \delta_{\bar{j}c}$ would choose to enter country c, and all movies with weighted qualities lower than $W_{\bar{j}} \cdot \delta_{\bar{j}c}$ would choose not to enter country c.

[17]The sequential entry assumption eases computational burden. Also, Einav (2010) provides evidence that higher-quality movies have the power to choose their release times first in a market.

4.2.3 Budget Decision Stage

At the budget decision stage, all movies' genres (A_j) and quality production shocks ($\nu_{1,j}$ and $\nu_{2,j}$) are realized and are common knowledge. However, the movie-country specific random taste shocks, e_{jc}, are not yet realized. Because export decisions depend on the realization of these taste shocks, movie producers must form an expectation over the perceived qualities of all the movies released in the same period. The taste shocks follow normal distributions $e_{jc} \sim N(0, \rho_c)$ and the standard deviations, ρ_c, are country-specific.

In each country, all US-origin movies are potential entrants. Movie producers know the set of all US-origin movies and make budget decisions simultaneously. Movie j's producer chooses the optimal budget $\tilde{B}_j$ to maximizes its total expected return from all countries:

$$\tilde{B}_j = \arg\max_{B_j} \sum_c E\left[\max\left\{R_{jc}(B_j, \bar{B}_{-j}) - F_c, 0\right\}\right] - B_j, \tag{10}$$

where the expectation is over the joint distribution of the movie-country taste shocks, $\{e_{jc}\}_{j \in J_{US}}$, of all US-origin movies. The model further assumes that the qualities and releases of local movies are exogenous. For any given set of taste shocks, $\{e_{jc}\}_{j \in J_{US}}$, and budget investments, $\{B_j\}_{j \in J_{US}}$, a producer can calculate the revenues conditional on entry (R_{jc}) and make its export decisions as described in Section 4.2.2.

Given the distributions of movie-country taste shocks, a movie's expected return is a function of all other movie's budgets $\bar{B}_{-j}$. Therefore, movie j's optimal budget is the best response to all other movies' budgets, $\tilde{B}_j(\bar{B}_{-j})$.

A *Production Budget Nash Equilibrium* is a set of budgets $\{B_j^*\}_{j \in J_{US}}$, where

$$B_j^* = \tilde{B}_j(B_{-j}^*), \forall j \in J_{US}. \tag{11}$$

The Nash Equilibrium is a fixed point of all movies' budget best response functions.

5 Estimation Procedure

In this section, we describe and discuss the estimation procedure. We first estimate the demand model in Equation (4), then use the demand estimates to construct movie j's price-adjusted perceived quality in country c, $\delta_{jc} = \beta_0 + \phi y_c + \xi_{cj}$.

As for the supply model, given the instrumental variable z_j, we use simple OLS regressions to estimate Equations (6) and (7). Then, we use the estimates to recover the omitted production shocks, $\hat{\nu}_{1,j}$ and $\hat{\nu}_{2,j}$. Under the assumptions that all potential US-origin movies are released in the US, we can use a control-function regression to directly estimate Equation (8) for the US market. However, we cannot use the same approach for other countries because not all US-origin movies are exported to every foreign country. The endogenous export decisions are likely to bias production function estimations due to the selection effect.

For all non-US countries, we use a simulated method of moments (SMM) procedure to jointly estimate the revenue weight W_j's, fixed costs F_c's, and the set of supply-side parameters, Θ. The set, Θ, includes the quality production parameters, $\{\mu_c, \gamma_{1r}, \gamma_{2r}, \gamma_{3r}, \tau_{1r}, \tau_{2r}, \chi_1, \chi_2\}$, and country specific taste shock standard deviation parameters, ρ_c's.

In the SMM procedure, we simulate the model N times for any given parameter set Θ.[18] In the n^{th} simulation, we first randomly draw a set of movie-country taste shocks $\{e_{jc}^n\}$ given the standard deviation parameter ρ_c. Then, we use Equation (8) to construct movie j's would-be quality in country c, $\tilde{\delta}_{jc}^n$. In each country, holding local movies exogenous, Hollywood movies make export decisions sequentially as described in Section 4.2.2.

We define movie j's worldwide box-office revenue in the n^{th} simulation, $\widetilde{RW}_j^n$, to be the sum of its weighted box-office revenue from all countries, conditional on entry:

$$\widetilde{RW}_j^n = W_j \sum_c \max\{\tilde{R}_{jc}^n - F_c, 0\}, \tag{12}$$

where $\tilde{R}_{jc}^n$ is a function of all movies' budgets B_j and random taste shocks $\{e_{jc}^n\}_{j \in J_{US}}$.

As described in Section 4.2.3, when making budget decisions, movie producers do not observe country-specific taste shocks and must form expectations over all possible outcomes.

[18]In practice, we use $N = 10,000$.

Numerically, movie j's worldwide expected profit is

$$E\pi_j = \frac{1}{N}\sum_{n=1}^{N}\left[\sum_c \widetilde{RW}_j^n\right] - B_j. \tag{13}$$

A high-budget movie is likely to have high perceived qualities in all countries. A low-budget movie can also potentially draw a high taste shock to obtain a high perceived quality in a country. Therefore, every movie has a strictly positive probability of being exported to any country at the budget decision stage. Positive entry probabilities ensure the expected profit functions are smooth, thus enabling the use of first-order conditions to solve the Nash Equilibrium. Solving the first-order conditions, we have

$$B_j = W_j \frac{1}{N}\sum_{n=1}^{N}\sum_c p_c M_c \tilde{s}_{jc}^n \tilde{\eta}_{jc}^n, \tag{14}$$

where $\tilde{s}_{jc}^n$ is movie j's market share in country c and $\tilde{\eta}_{jc}^n$ is the budget elasticity of demand. The budget elasticity is a function of production budgets, market shares, and demand parameters.[19] A higher budget elasticity means that a movie's perceived quality and demand are more responsive to budget changes. As we will discuss later, the difference in budget elasticities between Action and Non-Action movies plays a crucial role in explaining the difference in budgets and box-office performances between the genres.

In Equation (14), ticket prices (p_c) and market sizes (M_c) are observables in the data. We assume that the production budgets in data, B_j's, are movie producers' optimal choices. We use Equation (14) to recover movie-specific revenue weight factors, W_j's. After recovering W_j, we use the zero-profit condition of the marginal movie in each country to back out the country-specific fixed costs, F_c,

$$F_c = \min_{j \in J_c}\{W_j \cdot R_{jc}\}. \tag{15}$$

We can recover both W_j's and F_c's for any given set of supply-side parameters, Θ. To estimate Θ, we simulate the model to match two sets of empirical moments. The first set of moments are on movies' box-office performances conditional on entry. The second set of moments are the average export probabilities. In every country, both sets of moments are

[19] The derivation of the budget elasticity, $\tilde{\eta}_{jc}^n$, is in the Appendix.

calculated for the four previously defined movie categories, "Low-Budget Action," "High-Budget Action," "Low-Budget Non-Action," and "High-Budget Non-Action. "

The supply-side parameters, Θ^*, minimizes the difference between the data moments $\overline{MS}$ and the average of simulated moments $\widehat{MS}^n(\Theta)$,

$$\Theta^* = \arg\min_{\Theta} \left[\left(\overline{MS} - \frac{1}{N} \sum_n \widehat{MS}^n(\Theta) \right)^T \cdot \Omega \cdot \left(\overline{MS} - \frac{1}{N} \sum_n \widehat{MS}^n(\Theta) \right) \right], \tag{16}$$

where Ω is the optimal weighting matrix.

Parameter identifications come from variations in empirical moments and our model structure. The variations of moments between movies of different genres and budget categories across regions help identify the region-specific quality production parameters. For instance, the difference in the average market shares between genres in a region helps identify γ_{1r}, and the differences in the average market shares between budget categories within the same genre help identify γ_{2r} and γ_{3r}.

However, we cannot observe movies' market shares in an export destination if they choose not to enter. We would get biased estimates of γ_{1r}, γ_{2r} and γ_{3r} if we only use market shares of the exporting movies. Movies decide not to export because they expect unfavorable box-office performances in these countries. Therefore, we can use the average export probabilities by genre to help identify the quality production functions. Suppose movies of a particular genre are disproportionate less likely to enter a region. In that case, we know that consumers in the region perceive the movie genre as having less quality. On the other hand, if higher budgets within a genre do not significantly improve the average export probabilities in a region, we know this genre has a small regional budget elasticity.

To use export probabilities to aid identification, we must control the distribution of country-specific random taste shocks. The variation in movie export decisions across countries helps identify the country-specific standard deviation parameters ρ_c. An export pattern consistent with the predicted movie qualities suggests that a country has a small standard deviation in random taste shocks, and vice versa.

6 Results

This section presents estimation results, explains the choices of instrumental variables, shows model goodness of fit, and discusses model implications.

6.1 Demand Estimates

We estimate the demand model using Equation (4). As discussed previously, movies' within market shares, $\ln\left(\frac{s_{jc}}{1-s_{0ct}}\right)$ and ticket price, p_c, are both endogenous variables. Following Einav (2007) and Ferreira, Petrin, and Waldfogel (2016), we use the log numbers of rival movies in country c as an instrument for within-market shares $\ln\left(\frac{s_{jc}}{1-s_{0c}}\right)$. The number of rival movies reflects the competitive pressure facing movie j in a country. We also use prices in other countries as instruments for p_c. Movie prices are highly correlated across different countries, but country-specific demand shocks are not correlated with movie prices in other countries..[20]

Table 3: Demand Model Estimates

		(1) No IV	(2) IV for Within Share	(3) IV for Price	(4) IV for Both
Income	(ϕ)	0.482***	0.501***	0.465***	0.511***
		(0.00173)	(0.002)	(0.002)	(0.002)
Ticket Price	(α)	-0.169***	-0.198***	-0.157***	-0.206***
		(0.001)	(0.002)	(0.001)	(0.002)
Market Expansion	(σ)	0.958***	0.742***	0.958***	0.757***
		(0.001)	(0.003)	(0.001)	(0.002)
Constant	(β_0)	-2.392***	-3.766***	-2.430***	-3.623***
		(0.007)	(0.017)	(0.007)	(0.017)

Notes: Table shows the estimates from the demand estimation with different IV controls. Column (1) reports the results with no IV. Column (2) reports the result with the number of rival movies as IV for the within market share. Column (3) reports the result with ticket prices in other countries as IV for price. Column (4) reports the result with both IVs. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3 reports the demand model estimates. Column 4 presents the demand estimates

[20]The instrumental variable choice follows Hausman, Leonard, and Zona (1994). Our demand estimation approach is also similar to Ferreira, Petrin, and Waldfogel (2016).

of the model using both instrumental variables. All parameters estimates are significant and have the expected signs. For comparison purposes, we have estimated three alternative models. Column 1 presents the estimates using OLS without any instruments. Column 2 presents the estimates using only the instrumental variable on within-market shares. Also, Column 3 presents the estimates using only the instrumental variable on movie ticket prices.

The "market expansion" effect parameter, σ, is 0.757 in Column 4, which is in line with the previous literature, such as Ferreira, Petrin, and Waldfogel (2016). When using the instrument variable on within-market shares, the estimated values of σ in Columns 2 and 4 are significantly lower than those in Columns 1 and 3. A lower σ implies a more significant market expansion effect, which means that a high-quality movie can attract audiences who would otherwise stay away. The difference in estimates, with and without using the number of rival movies as instruments, also suggests that competitive pressure matters in the movie industry. Although unobservable to econometricians, rival movies' demand shocks can significantly affect a movie's box-office performance.

The estimate for price coefficient, α, does not change significantly across the columns in Table 3. Using the instrumental variable on movie ticket prices does not change α because individual movies do not choose ticket prices. A movie theater typically charges the same price for all movies released at the same time. Therefore, idiosyncratic demand shocks do not cause large variability in observed ticket prices.

We use the Column 4 demand estimates in all subsequent estimations and counterfactual experiments.

6.2 Supply Estimates

We use the Simulated Method of Moments procedure detailed in Section 5 to estimate the quality production function parameters in Equation (8), which include the country fixed effects, genre fixed effects, budget intensity parameters, time trends, and movie-level unobserved quality shocks. The estimation takes into accounts the endogenous export choices.

As discussed in Section 4.2, we use a control function approach to recover movie-level unobserved quality shocks. We follow Ferreira, Petrin, and Waldfogel (2016) and use movie studio's overall production budget in the previous year, z_j, as an instrument. The idea is that movie studios have limited financial resources. The previous year's production budget can affect a studio's budget decisions this year, but it is not directly correlated with the studio's current-year movie qualities.[21]

Table 4 reports the estimates of coefficients on the genre, the logarithm of budget, and their interaction term across regions. The Action genre dummy variable is γ_{1r}. The estimated coefficient ranges from -3.662 in South America to -0.801 in the US. The estimates are statistically significant in all regions except for the US. Hence, in regions outside the US, Action movies have a lower average perceived quality than Non-Action movies, conditional on having low production budgets.

TABLE 4: Quality Production Function Estimates

		Asia	E. Europe	W. Europe	S. America	U.S.
Action	(γ_{1r})	-2.033***	-1.267***	-2.401***	-3.662***	-0.801
		(0.751)	(0.389)	(0.790)	(1.352)	(0.821)
ln(Budget)	(γ_{2r})	0.119***	0.133***	0.141***	0.103***	0.269***
		(0.025)	(0.029)	(0.022)	(0.020)	(0.019)
Action× ln(Budget)	(γ_{3r})	0.143***	0.081***	0.141***	0.214***	0.035
		(0.040)	(0.022)	(0.074)	(0.044)	(0.045)

Notes: Table shows the estimates from the quality production function estimation in different regions. All estimates control for country fixed effects and a time trend, as well as unobserved quality shocks $\hat{\nu}_1$ and $\hat{\nu}_2$. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

The estimated coefficient on the logarithm of budget, γ_{2r}, is positive in all regions. Because the marginal return to budget investment is significantly positive, movies with higher production budgets tend to have higher perceived qualities in every region.

The coefficient γ_{3r} is on the interaction term between the Action dummy and the logarithm of budget. The estimates change significantly across regions, ranging from 0.035 in

[21]One potential concern is that this instrumental variable may not satisfy the exclusion restrictions. In the movie industry, franchise movies are becoming increasingly popular. A movie studio may release a movie in one year and its sequel in the next year. When using the last year's studio budgets as an instrumental variable, studios with popular franchise movies can have disproportionately large budgets due to persistent productivity shocks. To test the robustness of our estimation results, we reestimate the model using an alternative instrumental variable – movie studios' numbers of wide-released movies from the previous year, which is less prone to violate the exclusion restrictions due to franchise movies. The Appendix Table A2 and Table A3 present detailed estimation results based on the alternative instrumental variable. Overall, the main estimation results are robust with respect to the alternative instrumental variables. Importantly, the alternative estimations confirm that the ratios of elasticities by genre are much higher in foreign regions than in the US. The specific choices of instrumental variables do not alter our insight into Globalization's role in the rise of Action movies in Hollywood.

the US to 0.214 in South America. A positive coefficient, γ_{3r}, means that the same budget increase would raise an Action movie's perceived quality more than that of a Non-Action movie, holding everything else the same. The between-genre difference in γ_{3r} within a region reflects the production technology difference by genre. For example, a higher budget investment in CGIs can significantly increase an Action movie's perceived quality. However, raising budgets by the same amount to hire dialogue coaches may have a much less effect on the perceived qualities of dramas or romantic comedies.

Countries vary in their market conditions and can differ in the numbers and qualities of local movies. Therefore, we cannot directly compare the quality production function estimates in Table 4 across regions. Instead, we construct a budget elasticity measure, $\eta_{jc} = \frac{\partial s_{cj}}{\partial B_j}\frac{B_j}{s_{cj}}$. Holding export decisions fixed, the budget elasticity, η_{jc}, measures the responsiveness of movie j's market share, s_{jc}, to a change in its production budget, B_j, in country c.[22]

Table 5: Mean Budget Elasticity Across Regions

	Asia	E. Europe	W. Europe	S. America	U.S.
Action	1.05	0.87	1.14	1.28	1.23
Non-Action	0.49	0.54	0.58	0.42	1.10
Action to Non-Action Ratio	2.16	1.59	1.97	3.03	1.12

Table 5 summarizes the average budget elasticities by genre and by region. The parameter γ_{3r} is the primary contributor to the difference in budget elasticity between genres. Because γ_{3r} is significantly greater than zero in all regions outside the US, Action movies have markedly higher budget elasticities than Non-Action movies in these regions.[23] For example, an one percent increase in an Action movie's budget would lead its market share (or box-office revenue) to increase by 1.05 percent on average in an Asian country. The

[22]If movie j is not released in country c, then $\eta_{cj} = 0$. This measure is an imperfect proxy of the "true" budget elasticity, which would incorporate the impact of budget on export decisions. We show the impacts of changing budgets on export decisions in the counterfactual exercise in Section 7.

[23]Action movies, on average, have higher budgets than Non-Action movies. We make two additional budget elasticity comparisons to see if the budget difference by genre matters. In the first comparison, we compare Action movies to a hypothetical set of Non-Action movies, which have identical budgets and export decisions but have a parameter value $\gamma_{3r} = 0$. In the second comparison, we compare Non-Action movies to a hypothetical set of Action movies, which have identical budgets and export decisions, but have budget slope parameters set to be $\gamma_{2r} + \gamma_{3r}$ as in Table 4. The alternative comparison results are presented in Table A4 in the Appendix. The elasticity differences between Action and Non-Action movies, holding budget and export decisions fixed, do not change very much.

increase is only 0.49 percent for an average Non-Action Movie in the same region.

Table 5 also presents the ratios of budget elasticities, which measure the relative responsiveness of market shares to budget changes by genre. For example, in Asian countries, for the same percentage increase in budget, the resulting percentage increase in an Action movie's market share is 2.16 times that of a comparable Non-Action movie. Interestingly, the ratios of elasticities are much higher in all foreign regions than in the US. Consequently, in many export destinations, as compared to the US, investments in Action movies have a much higher "bang for the bucks" than those in Non-Action movies.

One possible explanation of the difference in the ratios of budget elasticities across regions is the language barrier. The "official" language of most Hollywood movies is English, which is not commonly spoken in regions like Asia. For these regions, demands may be less responsive to the budget invested in improving movie dialogues in dramas or comedies than that invested to improve CGIs in Action movies.

To show language barriers matter to a movie's global performance, we present descriptive evidence using a screenplay dataset, which records the number of words spoken by main characters in movies.[24] A robust negative correlation exists between the average number of words spoken in Hollywood movies and how widely they are exported (see Table A5 in the Appendix). For example, movies exported to more than half of the Asian countries, on average, have 7.5 percent fewer words spoken than those exported to fewer than half of the Asian countries.

Due to Globalization, Hollywood movies are increasingly reliant on regions with high Action to Non-Action budget elasticity ratios, such as Asia. Market expansions in these foreign export markets further widen the gap between genres in budget elasticities. Also, budget elasticities determine movies' optimal production budgets, and in turn, their perceived qualities and export decisions. Based on this intuition, we show in Section 7 that Globalization can contribute significantly to the rise of Action movies in Hollywood.

[24]The screenplay data is from an online source, https://pudding.cool/2017/03/film-dialogue/index.html. The original data contains over 2,000 movies from the 1930s to 2015. We can match 413 movies in our sample. Every main movie character has at least 100 words of dialogue, and the actor can be cross-referenced in the IMDb. On average, a movie's main characters have approximately 10,000 words in total.

6.3 Goodness of Fit

The purpose of this section is two-fold. First, we show that the estimated model fits well the chosen empirical moments and other non-targeted moments. Second, we compare our model's goodness of fit to those of alternative models and show our model specification is necessary to fit well.

TABLE 6: Goodness of Fit

		Asia	E. Europe	W. Europe	S. America	U.S.
			Within Market Share			
Action High-Quality	Data	62.0%	43.2%	41.7%	45.4%	37.2%
	Model	63.9%	43.3%	42.3%	46.5%	37.6%
Action Low-Quality	Data	19.0%	22.5%	19.3%	19.2%	15.9%
	Model	18.8%	22.1%	19.9%	19.0%	17.5%
Non-Action High-Quality	Data	15.9%	26.7%	28.3%	25.7%	32.0%
	Model	16.5%	28.2%	30.6%	28.3%	29.9%
Non-Action Low-Quality	Data	3.0%	7.6%	10.7%	9.7%	14.9%
	Model	0.9%	6.5%	7.2%	6.1%	15.0%
			Ratio of Aggregate Box-office Revenues			
Model/Data		1.000	1.000	1.000	1.000	1.020
			Average Export Probabilities			
Action High-Quality	Data	93.2%	93.9%	94.3%	90.4%	100.0%
	Model	95.1%	95.2%	95.2%	95.0%	100.0%
Action Low-Quality	Data	86.8%	90.1%	91.8%	89.8%	100.0%
	Model	83.6%	85.7%	88.2%	87.8%	100.0%
Non-Action High-Quality	Data	59.7%	77.2%	83.2%	80.7%	100.0%
	Model	61.8%	82.1%	87.2%	85.1%	100.0%
Non-Action Low-Quality	Data	35.6%	37.0%	37.7%	36.9%	100.0%
	Model	34.3%	35.2%	36.2%	36.0%	100.0%

Notes: Movie qualities are not directly observed, so movie budgets in data are used as a proxy for quality. "High-quality" means that a movie has an above-median budget within its genre and release year. "Low-quality" is similarly defined.

The upper panel of Table 6 shows the goodness of fit to market shares by movie category and region. The four movie categories, "Low-Budget Action," "High-Budget Action," "Low-Budget Non-Action," and "High-Budget Non-Action," are defined in the same ways as in Table 2. The model targets the "within-industry" market shares in every country, so the four movie groups' market shares sum to one.[25] These moments discipline the model on its

[25] Therefore, the model fits only the markets shares of the first three movie categories.

ability to track movies' post-entry box-office performance. Aggregating to regional levels, the differences between data and model market shares are all within four percentage points.

The estimated model fits well not only the relative market shares by movie category, but also the overall market size of the movie industry – every country's aggregate box-office revenues in the sample years. The middle panel of Table 6 shows, by region, the ratio of the model-predicted total box-office revenues to the data. The model is right on target, as a ratio of one means that the model predictions perfectly coincide with the data moments. The model also fits well at the individual country level. For example, in our sample years, the US share of total worldwide box office revenue is 43.9 percent, and the Chinese share is 10.1 percent.[26] The respective model-predicted shares are 44.4 percent and 10.0 percent, which closely match the data.

Because movie export decisions are endogenous, our estimation also targets the average export probabilities by movie category in all forty-three foreign countries. As discussed previously, we assume all potential movies are released in the US market, so the US entry probabilities are always 100 percent and are thus excluded from the targeted moments. The lower panel of Table 6 shows that the model fits the average export probabilities reasonably well. At the regional level, the difference between the data export probabilities and the model predictions are all within five percentage points.

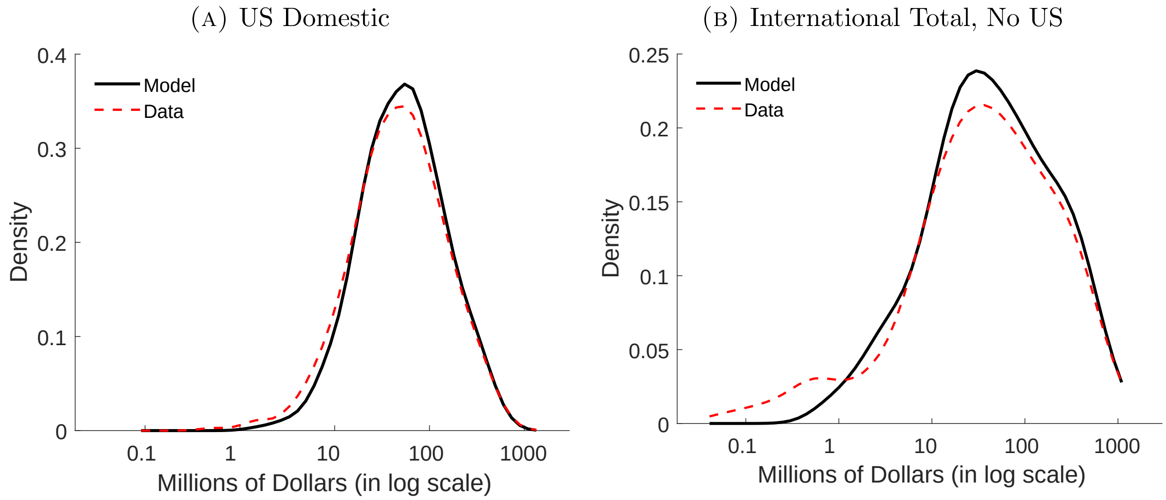
An essential feature of the movie industry is that box-office revenue distribution is highly skewed. The estimation does not explicitly target the distributions of movie box-office revenues in any market. However, Figure 1 shows that the estimated model fits these revenue distributions well.

Panel (A) of Figure 1 shows the model fits the distribution in the US domestic market. Especially, the model matches the right-tail of the distribution (i.e., top box-office "blockbusters"). Panel (B) of Figure 1 shows the model's fit to the distribution of aggregate box-office revenue in all the export markets. The data distribution is bimodal, with one peak in probability density between \$10 and \$100 million and another small peak on the left-tail of the distribution. The left-tail of the revenue distribution corresponds to those

[26] In this paper, we focus on only wide-release movies of US origin. If we consider all the movies, regardless of their countries of origin, the US share is 31.7 percent, and the Chinese share is 14.7 percent.

movies with very little international market exposure (i.e., movies with less than $1 million of export revenue). The model fits the distribution's right tail well but misses the small peak on the left-tail.

FIGURE 1: Revenue Distribution



In the data, movies with meager budgets are typically excluded from many export markets, causing a small peak on the distribution's left-tail. Our model does not reproduce the peak because model entries into foreign countries are probabilistic, and every movie has a strictly positive chance of entering into every country. Overall, missing the left-tail peak does not pose a big concern. Movies with less than $1 million of international box-office revenue account for only 2.4 percent of the US domestic revenue and only 0.02 percent of the aggregate export revenue.

One contribution distinguishing this paper from the previous literature, such as Ferreira, Petrin, and Waldfogel (2016), is that we explicitly model movies' export decisions. To assess the importance of endogenizing movies' export decisions, we alternatively estimate the model by directly regressing Equation (8) while holding the entry decisions fixed. Without considering how movies' perceived qualities, δ_{jc}, can endogenously affect the export decisions, the alternative model over-predicts movie export probabilities. For example, the alternative model predicts that the average export probability of Non-Action High-Quality movies in Asian countries is 90.6 percent, which is much higher than 59.7 percent in the data.[27]

[27]See more details in the Appendix. Table A6 and Table A7 show the alternative model estimates and

Previous studies typically have a genre fixed effect in quality production functions similar to parameter γ_{1r} in Equation (8). This paper builds on the existing literature and include an additional Action genre-specific budget investment parameter γ_{3r}. As discussed previously, the difference in γ_{3r} allows the relative budget elasticity by genre to vary across regions.

To validate the necessity of parameters γ_{3r} in the production function specification, we re-estimate the model while fixing $\gamma_{3r} = 0$ in all regions. We estimate the model using the same SMM procedure to fit the same data moments as described in Section 5. We find that the alternative model with $\gamma_{3r} = 0$ lacks the flexibility to account for the relative differences between Action and Non-Action movies. If the alternative model fits the relative market shares by genre reasonably well, it would severely under-perform in matching the relative export probabilities between genres. For instance, the difference between the average export probabilities of Action movies and Non-Action movies is 41 percent in the data. The benchmark model with flexible γ_{3r}'s fits well and produces a between-genre difference of 40.7 percent, while the alternative model with $\gamma_{3r} = 0$ predicts a difference of only 28.2 percent.[28]

7 Counterfactual Experiments

We conduct counterfactual experiments to understand the impacts of Globalization on the movie industry. This section shows how changes in foreign export markets affect budget allocations, export decisions, and box-office performances of Hollywood movies. Furthermore, we quantify the welfare implication of the rise of Action movies in Hollywood.

The counterfactual experiments hold fixed all the demand parameters, the quality production function parameters, the export destination entry costs F_c, the movie revenue weights W_j, and the qualities of non-Hollywood movies. We also use the same set of US-origin movies and the same country-specific random shock draws from the model estimation. For every counterfactual change, we re-solve the market equilibrium by optimizing budget and export decisions for all US-origin movies

goodness of fit, respectively.

[28]See more details in the Appendix. Table A8 and Table A9 show the alternative model estimates and goodness of fit, respectively.

7.1 Chinese Market Expansion

In the *Benchmark* counterfactual experiment, we vary the market size of one particular export destination - China. Along with the Chinese economy, the Chinese movie market has grown exponentially in the past 25 years, thanks in part to trade liberalization. The increasing exposure of Hollywood movies to the Chinese market is the epitome of Globalization in the movie industry.

To simulate the Chinese market's expansion, we vary the market size M_{China} by a factor, φ, while holding other parameters constant. We vary φ on a grid from zero to one.[29] We refer to the counterfactual world with $\varphi = 0$ as the *No China* world, and the world with $\varphi = 1$ as the *Baseline* world. In the *Baseline*, the Chinese market size is the same as in the data. Because the Chinese market data is not available for several years in our sample, we only use the most recently available years 2013-2016 for simulating the *Baseline* world.

As the Chinese market size grows, China becomes a more important source of Hollywood's box-office revenue. In the simulation, the Chinese share of total world box-office revenue increases from zero in the *No China* world ($\varphi = 0$) to 10 percent in the *Baseline* world ($\varphi = 1$) . Meanwhile, the US share falls from 52.5 percent to 44.4 percent, and the total share of all the other countries falls from 47.5 percent to 45.6 percent.

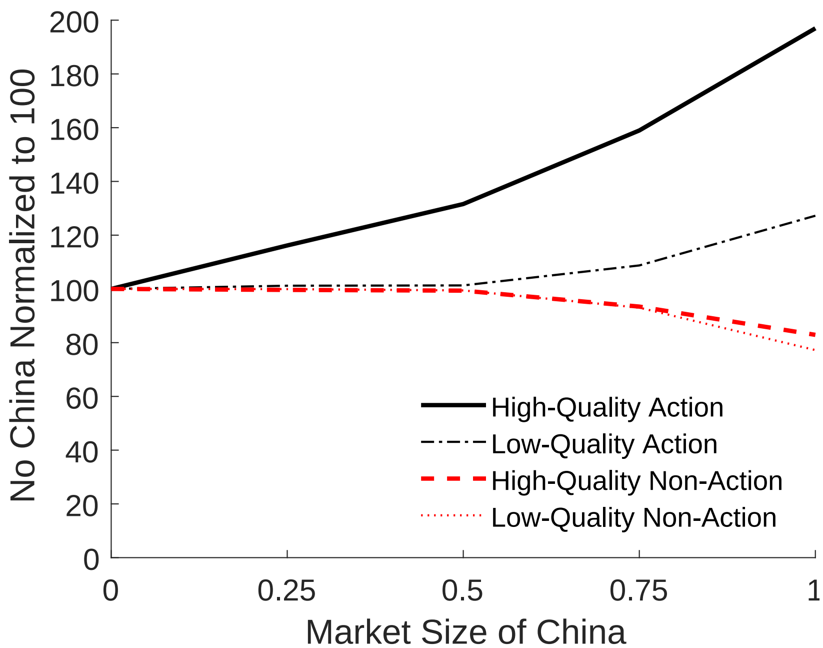
As φ increases from zero to one, the aggregate budget investment in Hollywood increases by 19.2 percent. Figure 2 compares the average budget changes by the four movie categories. In the counterfactual experiments, we hold fixed all movies' categories, defined the same ways as in Table 2. In Figure 2, the budget levels in the *No China* world are normalized to 100 to make the comparison across movie categories possible.

Figure 2 shows that Action movies, especially those of High-quality, benefit the most from the Chinese market expansion. While the Low-quality Action movies' average budget increases by about 27 percent, the average budget of a High-quality Action movie increases by almost 100 percent, going from the *No China* world to the *Baseline* world. Empirical evidence corroborates the finding here. For example, the top-grossing Action movie in 1995, "Batman Forever," had a budget of \$161 million (2019 dollar, inflation-adjusted), while top

[29] The Chinese movie market has experienced both demand growth and fewer trade restrictions. A higher φ captures the demand growth. Section 7.1.1 discusses the impacts of trade restrictions.

action movies in recent years, such as "Avengers: Infinity War," have production budgets topping $300 million.

Figure 2: Movie Budget Changes By Genre and Quality



Due to higher Action movie investments and competition, Non-Action movies face lower marginal returns-to-investment. Going from the *No China* world to the *Baseline* world, the High-Quality Non-Action movies' average budget declines by 17 percent and that of Low-Quality Non-Action movies declines by 23 percent.

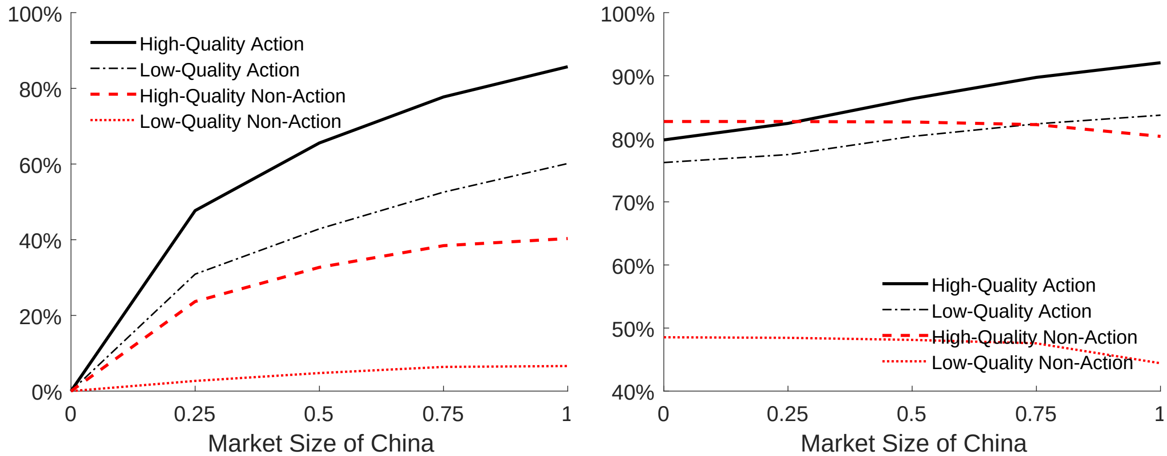
As discussed in Section 6.2, the ratio of budget elasticities between Action and Non-Action movies is much higher in Asia than in the US. Intuitively, compared to their US counterparts, the Chinese audiences value more of an additional dollar spent on Action movies than an additional dollar spent on Non-Action movies. As the Chinese market grows, Hollywood producers increasingly cater to Chinese demand and steadily allocates more budget investments to Action movies relative to Non-Action movies.

The Chinese market expansion also affects movie export decisions. Panel (A) of Figure 3 shows the export probability changes in China as φ increases from zero to one. As expected, High-Quality Action movies are the most likely to be exported to China. Even if China is only a quarter of its *Baseline* size, these movies have a 47.7 percent chance of being exported to China. The export probability would rise to 85.7 percent at the *Baseline* equilibrium.

Low-Quality Action movies are also significantly more likely to be exported to China, and their average export probability increases from zero to over 60 percent.

FIGURE 3: Export Probability

(A) China (B) All Other Foreign Markets



In contrast, Non-Action movies are less likely to be exported to China. High-Quality Non-Action movies' chance of being exported to China is only 40 percent at the *Baseline* equilibrium. Low-Quality Non-Action movies would never take off in China, having only a 7 percent chance of being exported to China even in the *Baseline* world.

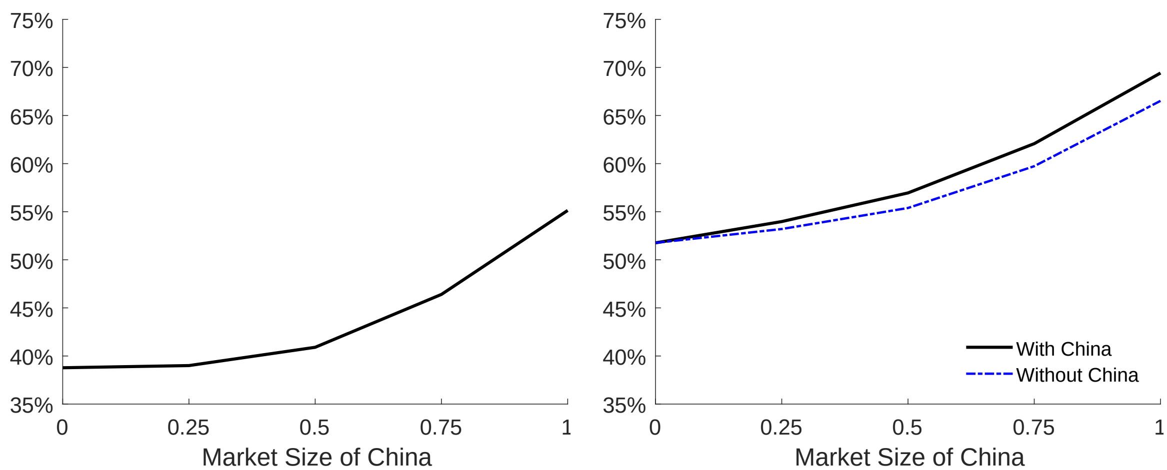
The Chinese market expansion affects movie exports not only in China but also in other international destinations. Panel (B) of Figure 3 shows the export probabilities averaged across all countries, excluding China and the US. As φ increases from zero to one, the High-quality and Low-quality Action movies' average export probabilities increase by 12.3 percent and 7.6 percent, respectively. In contrast, the High-Quality and Low-Quality Non-Action movies' average export probabilities decrease by 2.3 percent and 5.4 percent, respectively. These export destinations' market sizes and other characteristics are fixed in the counterfactual experiment, so the export probability changes are the result of movie budget changes.

Overall, the Chinese market expansion raises both budget investments and export probabilities of Action movies relative to those of Non-Action movies, thus contributes to a rise of Action movies in Hollywood. Namely, Action movies' market shares increase significantly in both the US domestic and foreign export markets.

In Panel (A) of Figure 4, comparing the *No China* world to the *Baseline* world, the market share of Action movies in the US domestic box-office increases from 38.7 percent to 55.1 percent - an increase of 16.4 percentage points. Action movies are more popular in foreign markets than in the US. Panel (B) similarly shows that Action movies gaining market shares in all foreign export markets as the Chinese market expands. In particular, the market share of Action movies in the aggregate export-market box-office would increase from 51.8 percent to 70.0 percent - an increase of 18.2 percentage points. Excluding the Chinese market, Action movies' market share would still increases from 51.8 percent in the *No China* world to 66.5 percent in the *Baseline* world.

FIGURE 4: Action Movie Market Share of Box-office Revenue

(A) Dometic US Market (B) All Other Foreign Markets



As φ increases from zero to one, the US domestic market share of High-Quality Action movies increases from 21.4 percent to 37.6 percent. The rise of 16.2 percentage points accounts for almost all the increase in Action movies' overall domestic market share. High-Quality Action movies also contribute the most to the increase in foreign market shares.[30]

Furthermore, the counterfactual results match an empirical trend – Hollywood has become increasingly reliant on a few "Tent-pole" Action movies. In the *No China* world, of the top ten movies as measured by annual domestic box-office revenue, an average of 7.25 movies are Action movies. In the *Baseline* world, all ten movies are Action movies. Similarly, of the top twenty movies, 9.75 movies are Action movies in the *No China* world, while 18.25 movies are Action movies in the *Baseline* world.

[30]In fact, Low-Quality Action movies have a decline of 2.5 percentage points in foreign market shares.

To further validate our counterfactual results, we conduct two simple comparison tests with the data. First, we compare the simulated Action movie market shares in the *Baseline* to the empirical market shares in the 2013-2016 period. From the data, Action movies have an aggregate market share of 53.0 percent in the domestic market and 70.0 percent in the foreign export markets. The model simulated market shares perfectly match the data.

It is not surprising that the simulation does well in the *Baseline* world because the model estimation targets movies' within market shares in recent years. Therefore, we also check the model prediction of Action movie market shares in the *No China* world. Hollywood movies began to enter China in 1995. Coincidentally, our data source, *The Numbers.com*, only reports reliable US domestic box-office data starting in 1995.[31] Based on *The Numbers.com*, the domestic market share of Action movies in 1995 was 34 percent. In comparison, the model-simulated domestic market share of Action movies in the *No China* world is 38.7 percent. Even when the model estimation does not target any moments in 1995, the counterfactual simulation comes reasonably close.

The counterfactual experiments primarily focus on the expansion of China. We choose China because it is the fastest-growing major economy, and the Chinese movie market has become the second-largest in the world. However, the relationship between export market expansion and Action movies' rise is not specific to the Chinese market. We have conducted alternative counterfactual experiments with hypothetical market expansions in South America, Eastern Europe, Western Europe, and other Asian countries. These counterfactuals show that comparable market expansions in these regions can similarly lead to large increases in Action movies' market shares.[32]

The Chinese market also poses unique challenges to Hollywood movies that we have not considered thus far. We will discuss these challenges next.

7.1.1 Chinese Import Quota

China has various trade restrictions, in particular, import quotas on non-Chinese movies. Over the years, the Chinese trade restrictions tend to lessen. In particular, the increases in

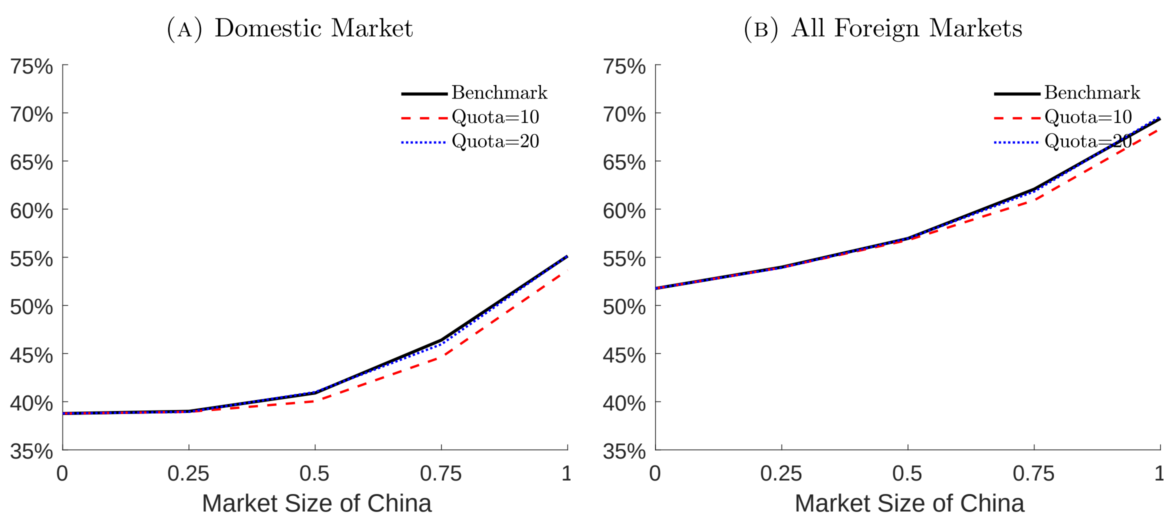
[31] Unfortunately, we cannot directly compare the foreign market shares of Action movies in 1995, because our data sources do not report reliable foreign box-office data until 2007.

[32] Please see Figure A1 in the Appendix.

the number of Chinese import quotas can potentially confound our results' interpretation. To address the potential concern, we conduct two additional counterfactual experiments. In the first alternative counterfactual experiment, China imposes a quota of ten movies – only the top ten movies in terms of weighted quality ($W_j \delta_{jc}$) are allowed to enter the Chinese market. In the second experiment, we double the number of quotas to 20.

Figure 5 compares the changes in Action movies' market shares with Chinese quotas to those under the *Benchmark* model without quotas. In the counterfactual with a stringent import quota of ten movies, Panel (A) shows that the domestic market share of Action movies would increase by 14.9 percentage points, going from the *No China* world to the *Baseline* world. In other words, the increase in Action movies' domestic market shares in the alternative counterfactual experiment is 91.1 percent of the increase in the *Benchmark* experiment. Similarly, Panel (B) shows that the increase in Action movies' foreign market shares in the "ten-quota" counterfactual is 94.0 percent of the *Benchmark* increase.

FIGURE 5: Action Movie Market Share Comparison - Chinese Import Quotas



Furthermore, when we increase the Chinese import quota to 20, the increases in Action movies' market share are virtually the same as those in the *Benchmark* experiment. Clearly, the Chinese import quotas matter very little.

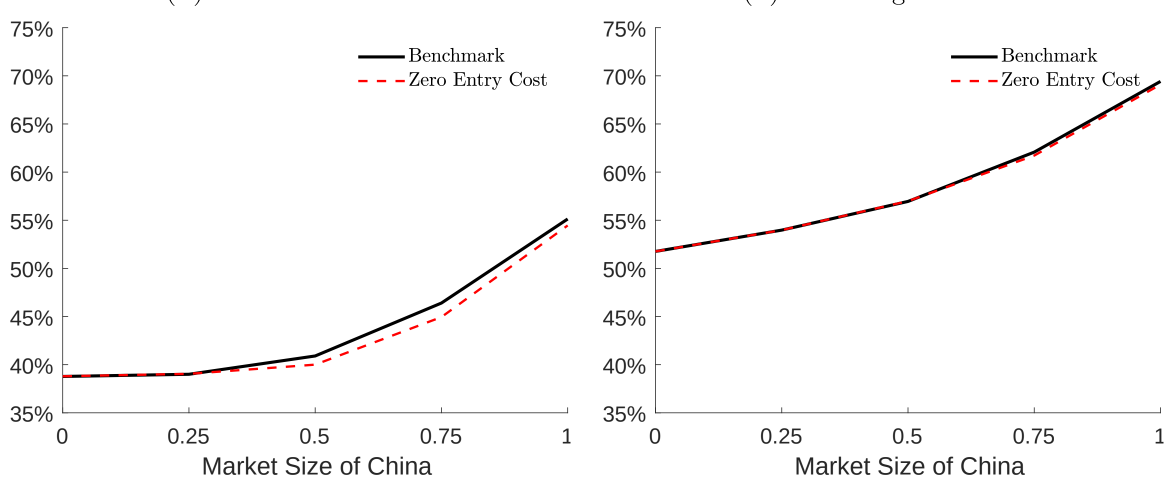
Concerning changes in trade restrictions overtime, the counterfactual results with Chinese import quotas prove the robustness of two main results in the paper. First, the Chinese market expansion contributes significantly to the rise of Action movies in Hollywood. Second, the rise of Action movies is mostly due to the disproportionate market share increase of a few "High-Quality" blockbusters.

7.2 Intensive vs. Extensive Margins

Our model incorporates both the intensive and extensive margins in explaining the rise of Action movies. On the intensive margin, the ratio of Action to Non-Action budget elasticities is higher in Asia than in the US. The Chinese market expansion raises the relative marginal returns to invest in Action movies. Producers would invest more intensively in Action movies regardless of entry costs to export markets. In contrast, on the extensive margin, entry costs are a critical factor in the rise of Action movies. Action movies are more likely to enter the export markets because they have a higher average quality and can remain profitable after paying the entry costs. As a result, a higher exposure to export markets causes industry resource reallocation towards Action movies. To identify the relative importance of these two margins, we re-simulate the model by shutting down one margin at a time.

FIGURE 6: Action Movie Market Share Comparison - Zero Entry Cost

(A) Domestic Market (B) All Foreign Markets



To test the importance of the extensive margin, we conduct an alternative counterfactual experiment by setting China's fixed entry cost (F_{China}) to zero. In the *Zero-entry-cost* counterfactual, all movies produced in the US can freely enter the Chinese market regardless of genres or qualities. Hence, the Chinese market expansion does not favor one group of movies over the others in terms of export probabilities.

As in the *Benchmark* counterfactual experiment, we vary the Chinese market size by a factor of $\varphi \in [0,1]$. Figure 6 compares Action movies' aggregate market share changes between the *Zero-entry-cost* and the *Benchmark* experiments. Going from the *No China* world ($\varphi = 0$) to the *Baseline* world ($\varphi = 1$), the *Benchmark* predicts increases in Action movies' shares by 16.4 and 17.7 percentage points in domestic and foreign markets, respectively. In comparison, the corresponding increases are 15.7 and 17.3 percentage points in the *Zero-entry-cost* counterfactual. The model without the extensive margin captures 95.8 percent of the increase in the domestic market and 98.1 percent of the increase in the foreign market. We can therefore conclude that the extensive margin does not contribute significantly to the rise of Action movies in Hollywood.

To investigate the intensive margin, we conduct two sets of counterfactual experiments regarding the relative difference in budget elasticities between genres and across regions. In particular, we manipulate γ_{3r} in the Chinese quality production function (Equation (8)), while holding all other countries' parameters the same as in the *Benchmark*.

The first set of counterfactual experiments eliminates the between-genre difference in budget elasticity in China. We set $\gamma_{3,China} = 0$, so a budget increase would have the same marginal effect on both movie genres' perceived qualities in China. The second set of counterfactual experiments eliminates the regional difference in budget elasticities by setting $\gamma_{3,China}$ to be the same as $\gamma_{3,US}$ in the US. In both counterfactual experiments, we make an additional adjustment to the Action movie fixed effect in China, $\gamma_{1,China}$, to keep the average perceived quality of Action movies in China the same as in the *Benchmark*.

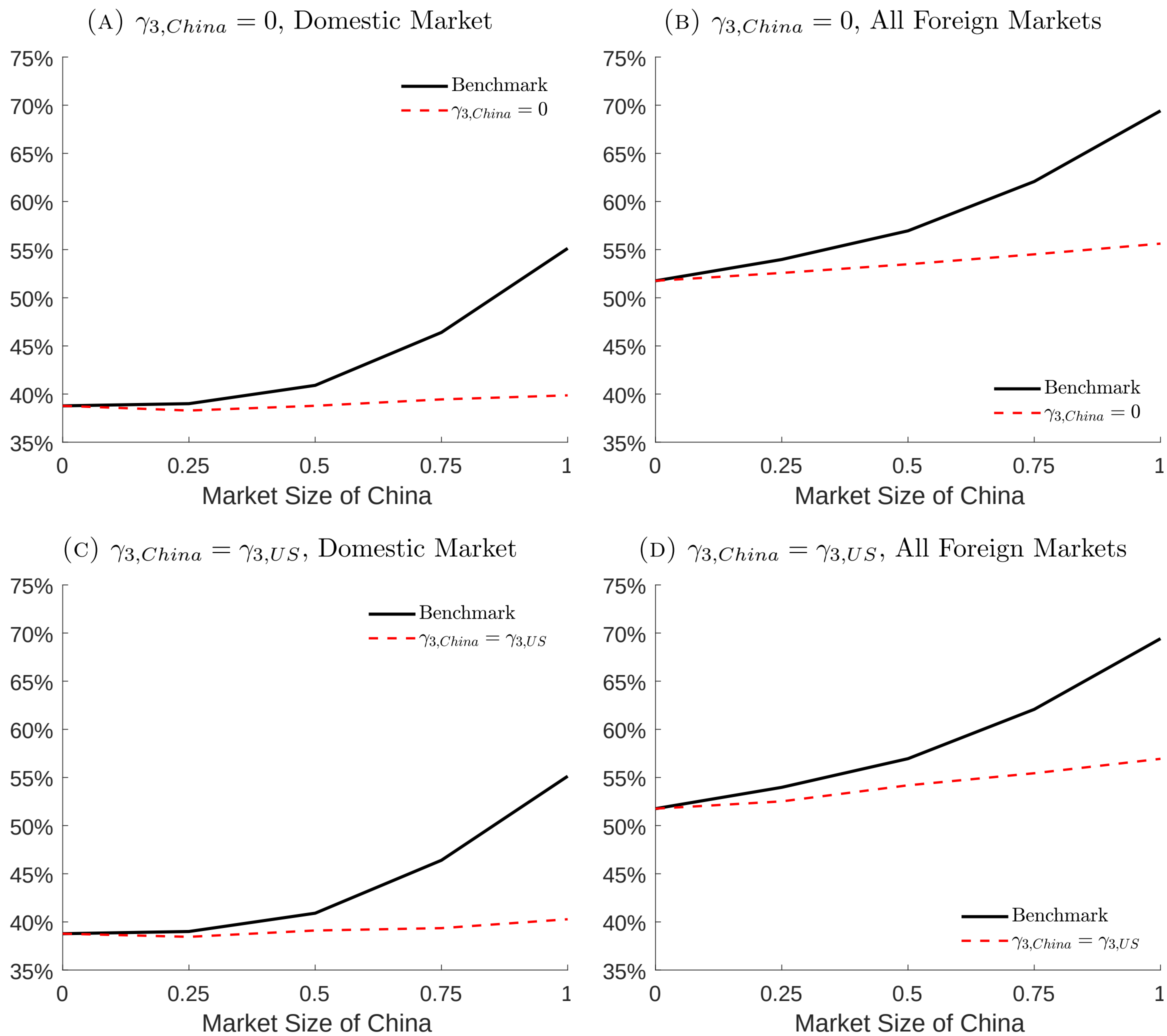
Panels (A) and (B) of Figure 7 show the changes in Action movies' market shares when $\gamma_{3,China} = 0$. As the Chinese market expands, Action movies' domestic market share increases by 1.1 percentage points, significantly lower than the 16.4 percentage points in the *Benchmark*. In foreign export markets, Action movies' market share increases by 3.9 percentage points, also much less than the 20.2 percentage points in the *Benchmark*.[33]

Panels (C) and (D) of Figure 7 show the changes in Action movies' market shares when

[33] We have also estimated an alternative model with $\gamma_{3r} = 0$ in all regions. The counterfactual experiment results are similar using the alternative parameters. Action movies' market shares increase by only 2.0 and 6.2 percentage points in the domestic and foreign export markets, respectively.

$\gamma_{3,China} = \gamma_{3,US}$. Going from the *No China* world to the *Baseline* world, Action movies' overall market shares increase by 1.5 and 5.2 percentage points in the domestic and foreign export markets, respectively. Similarly, the increases in Action movies' market shares are much smaller than those in the *Benchmark*.

FIGURE 7: Action Movie Market Share Comparison - Genre and Regional Differences



By adjusting $\gamma_{1,China}$ in the two sets of counterfactuals, we keep the average qualities of Action movies the same as in the *Benchmark*. In other words, Action movies still hold significant advantages in their perceived qualities over Non-Action movies. However, without the relative budget elasticity differences by genre across regions, a higher average quality of Action movies contributes very little to the increases in their market shares.

In summary, our results suggest that Globalization leads to the rise of Action movies mostly through the intensive margin. In particular, the difference in relative budget elasticities by genre across regions can explain up to 93.3 percent of the increase in Action movies domestic market share and up to 80.7 percent of the rise in foreign export markets.[34] To the best of our knowledge, this paper is the first to quantify the impact of the Chinese market expansion on the shift in relative investment intensity between Action and Non-Action movies, which is a determining factor behind the rise of Action movies in Hollywood.

7.3 Industry Concentration

As previously discussed, Globalization can lead the industry to increasingly focus on a few "tent-pole" movies, overwhelmingly of the Action genre. To establish the industry outlook with the likely Chinese market expansion in the future, we simulate the model and compute two industry concentration measures. Table 7 shows the Herfindahl-Hirschman Index (HHI) and the Top-ten movie concentration ratio, in the *No China*, the *Baseline*, and the *China×2* worlds. In the *China×2* world, the size of the Chinese market is twice that in the *Baseline*. We calculate each concentration measure for the aggregate world market, the US domestic market, and foreign export markets.

Table 7 confirms that Globalization can lead to a higher industry concentration, not only in the foreign markets but also in the US domestic market.

TABLE 7: Industry Concentration

	HHI			Concentration Ratio, Top 10		
	All	Domestic	Foreign	All	Domestic	Foreign
No China	162.75	133.73	210.73	28.4%	23.0%	34.4%
Baseline	212.80	190.58	255.95	35.7%	31.7%	41.4%
China × 2	301.76	266.75	332.17	44.6%	42.0%	46.9%

Notes: The table shows the Herfindahl Index and Concentration Ratio of the top 10 movies in the industry.

Not surprisingly, a further expansion of the Chinese market can raise market concentration even higher. The total US domestic market share of the top ten movies increases by 8.7 percentage points, going from the *No China* world to the *Baseline* world, and further

[34]These are based on Panels (A) and (B) of Figure 7.

increases by 10.3 percentage points in *China × 2* world. In comparison, the total foreign export market share of the top ten movies increases by 7 percentage points, going from the *No China* world to the *Baseline* world, and further increases by 5.5 percentage points in *China × 2* world. Interestingly, the traditionally more competitive US domestic market is consolidating and fast converging to the same level of concentration as the rest of the world. Most of the top movies are Action movies, which have relatively higher perceived qualities in foreign export markets than in the US. As a result, the top movies are likely to experience a higher degree of decreasing marginal return to budget investment in foreign markets, leading to a relatively smaller increase in concentration measures.[35]

7.4 Consumer Welfare

This subsection evaluates the consequences of a rise in Hollywood Action movies on consumer welfare both in the US and abroad. We use the utility function in Equation (1) to compute consumer surpluses. Following the standard nest logit model, the average consumer surplus in a particular country c is

$$\tilde{U}_c = \log\left[\left(\sum_j pr_{jc} \cdot \exp\left(\frac{\theta_{jc}}{1-\sigma}\right)\right)^{1-\sigma} + 1\right],$$

where pr_{jc} is the estimated export probability of movie j in country c.

Table 8 shows the regional consumer welfare changes from the *Baseline* world. For example, the upper panel shows that consumers in all regions prefer the *Baseline* world to the *No China* world. If the Chinese market disappears, consumers would suffer a loss ranging from \$0.53 in Asia to \$0.12 in the US per person. These welfare losses are quite significant, considering that the welfare loss is for every individual in the entire population of a region, regardless of whether an individual goes to theaters or not. Compared to the *Baseline*, these amount to 9.36 percent welfare loss in Asia and 1.91 percent in the US.

A Chinese market expansion affects consumer welfare globally mainly in two ways. First, an increase in Chinese demand expands the global consumer base, which leads to marginal

[35] Beyond industry concentration, the overall market shares of Action movies would rise more if the Chinese market size further expands. Please see Appendix Table A2 for a detailed discussion.

revenue and budget investment increases in Hollywood. Based on our counterfactuals, going from the *No China* world to the *Baseline* world, the aggregate industry budget increases by 19.2 percent. The industry-wide budget investment increase would improve average movie qualities and raise consumer welfare everywhere in the world.

On the other hand, the fast-rising Chinese demand shifts the relative regional shares of Hollywood box-office revenue. As discussed previously, the industry experiences a relative reallocation of budget investment from Non-Action to Action movies. The change in industry movie compositions can affect consumer welfare differently across countries.

Table 8: Consumer Welfare Changes

	Asia	E. Europe	W. Europe	S. America	U.S.
No China World	-\$0.53	-\$0.28	-\$0.25	-\$0.28	-\$0.12
	(-9.36%)	(-5.44%)	(-4.67%)	(-4.88%)	(-1.91%)
Proportional Budget Increase	-\$0.35	-\$0.12	-\$0.07	-\$0.10	\$0.12
	(-6.16%)	(-2.38%)	(-1.39%)	(-1.68%)	(1.93%)
US Market Expansion	-\$0.16	-\$0.03	\$0.03	\$0.07	\$0.08
	(-2.62%)	(-0.53%)	(0.58%)	(1.54%)	(1.30%)

Notes: The table shows the changes of per-consumer welfare in terms of US dollars from the baseline equilibrium. Percentage changes of welfare are reported in parenthesis.

Previous international trade literature has studied in-depth the effect of Globalization in expanding the international consumer base. Our contribution is to further the understanding of intra-industry resource reallocation across different types of cultural goods. Therefore, we focus on the latter effect and study how a disproportionate increase in Action movies can affect consumer welfare differently across regions. To isolate the effect of the Action movies' rise, we control the aggregate increase in industry budgets due to a higher overall global demand using two alternative counterfactual experiments.

In the *Proportional Budget Increase* counterfactual experiment, we raise all movies' budgets in the *No China* world by the same proportion, 19.2 percent. As a result, the aggregate industry budget exactly matches that in the *Baseline*, but the relative budget allocations remain the same as in the *No China* world. The *Proportional Budget Increase* case, which ignores any regional differences in quality productions, is unlikely to be an equilibrium outcome. Nevertheless, comparing the consumer welfare between the *Proportional Budget In-*

crease and the *Baseline* cases help determine the impact of relative budget reallocation from Non-Action to Action movies.

As Table 8 shows, the average consumer welfare in the *Proportional Budget Increase* case is lower in all foreign exporting regions than those in the *Baseline*. The decreases range from 1.39 percent in Western Europe to 6.16 percent in Asia (excluding China). In Asia, for example, the per-consumer welfare is \$0.35 higher in the *Baseline* than in the *Proportional Budget Increase* case. The higher consumer welfare in the *Baseline* is entirely due to Action movies having relatively higher budget investments.[36]

To understand the importance of relative budget reallocation, we do a simple decomposition exercise. An average Asian (excluding the Chinese) consumer's welfare gain from the *No China* world to the *Baseline* is \$0.53. Of this overall welfare gain, 66 percent (=\$0.35/\$0.53) comes from the rise of Action movies, and the remainder 34 percent comes from the industry-wide budget increase.

In contrast, the relative budget reallocation from Non-Action to Action movies hurts domestic consumers. In the US, the per-consumer welfare is \$0.12 (1.93 percent) lower in the *Baseline* than in the *Proportional Budget Increase* case. The US consumers have less proclivity for Action movies. Because of budget reallocation, the welfare loss due to relatively lower movie qualities in other genres more than offset the welfare gain from better quality Action movies. Interesting, the welfare impacts of the movie industry Globalization is heterogeneous across different regions in the world.

Because the *Proportional Budget Increase* case is not an equilibrium outcome, we also consider an alternative equilibrium in the *US Market Expansion* counterfactual experiment. In the *US Market Expansion* case, we consider a market expansion in the US instead of China. In particular, we hold the Chinese market size to be zero and increase the US market size until the equilibrium aggregate budget exactly matches that in the *Baseline*.[37]

[36] The Non-Action movies' budgets would be at least 35 percent higher in the *Proportional Budget Increase* case than the *Baseline*. Meanwhile, the average High-quality Action movie budget would be 78 percent lower. Furthermore, in the *Proportional Budget Increase* case, the Action movies' domestic market share is 39.4 percent, and their foreign market share (excluding China) is 54.1 percent. In the *Baseline* equilibrium, Action movies have substantially higher market shares, which are 55.1 percent and 66.5 percent (excluding China), respectively.

[37] To match the *Baseline* aggregate industry budget (a 19.2 percent increase in the budget), we increase the US market size by 19.3 percent.

As mentioned in Section 6.2, the budget elasticity ratio between Action and Non-Action movies is much smaller in the US (1.12) than in China (2.16). Therefore, the US market expansion leads to a lower increase in Action movie shares.[38]

Table 8 shows that consumers in Asia and Eastern Europe are better off in the *Baseline* world. However, consumers in Western Europe, South America, and the US are better off in the *US Market Expansion* world. In summary, Globalization leads to the rise of Action movies in Hollywood, which can significantly benefit some international consumers. However, the distribution of welfare gain is not even across regions. Consumers benefit the most in regions where Hollywood Action movies are highly popular, such as in Asia. Consumers in other regions, especially the US domestic market, would benefit less and might even suffer a welfare loss.

8 Conclusion

This paper investigates the causal effect of Globalization on the rise of Action movies in Hollywood. We develop a structural model of movie demand and supply. The model explicitly considers producers' endogenous budget investment and export decisions. For movie-quality production, the model incorporates heterogeneous budget elasticities by genre across different countries.

The paper's findings suggest that Hollywood studios respond to Globalization by reallocating budget from Non-Action to Action movies. The resource reallocation across different types of products results mainly from the intensive rather than the extensive margin. Producers disproportionately increase budget investments in a few high-quality Action movies. The rise in Action movies leads to significant increases in consumer welfare in export regions but can hurt domestic consumers in the US.

In terms of future research, we can extend our work to consider movie serialization and franchises. Marvel Studios and Disney's recent developments have shown that Action movies have tremendous potentials for serialization in terms of sequels, prequels, and reboots. While

[38]In the *US Market Expansion* case, the domestic market share of Action movies is 51.9 percent, and the foreign market share (excluding China) is 62.2 percent. The *Baseline* Action move market shares are higher, which are 55.1 percent and 66.5 percent (excluding China), respectively.

movie franchises are becoming more dominant in the box office, consumers increasingly criticize Hollywood for its lack of originality. Building on previous marketing literature, such as Sood and Drèze (2006), Basuroy and Chatterjee (2008), and Hennig-Thurau, Houston, and Heitjans (2009), future projects can extend our model framework to study movie franchises' effects on industry concentration and consumer welfare by adding dynamic releasing decisions.

References

Ainslie, A., X. Dreze, and F. Zufryden (2005): "Modeling Movie Life Cycles and Market Share," *Marketing Science*, 24(3), 508–517.

Basuroy, S., and S. Chatterjee (2008): "Fast and Frequent: Investigating Box Office Revenues of Motion Picture Sequels," *Journal of Business Research*, 61(7), 798–803.

Berry, S. T. (1994): "Estimating Discrete-choice Models of Product Differentiation," *The RAND Journal of Economics*, 25(2), 242–262.

Ciliberto, F., C. Murry, and E. T. Tamer (2018): "Market Structure and Competition in Airline Markets," mimeo, Harvard University.

Dalton, J. T., and T. C. Leung (2017): "Strategic Decision-Making in Hollywood Release Gaps," *Journal of International Economics*, 105, 10–21.

Danaher, B., and J. Waldfogel (2014): "Reel Piracy: The Effect of Online Film Piracy on International Box Office Sales," working paper.

De Vany, A., and W. D. Walls (1996): "Bose-Einstein Dynamics and Adaptive Contracting in the Motion Picture Industry," *The Economic Journal*, 106(439), 1493–1514.

——— (1999): "Uncertainty in the Movie Industry: Does Star Power Reduce the Terror of the Box Office?," *Journal of Cultural Economics*, 23(4), 285–318.

——— (2004): "Motion Picture Profit, the Stable Paretian Hypothesis, and the Curse of the Superstar," *Journal of Economic Dynamics and Control*, 28(6), 1035–1057.

Einav, L. (2007): "Seasonality in the U.S. Motion Picture Industry," *RAND Journal of Economics*, 38(1), 127–145.

——— (2010): "Not All Rivals Look Alike: Estimating an Equilibrium Model of The Release Date Timing Game," *Economic Inquiry*, 48(2), 369–390.

Ferreira, F., A. Petrin, and J. Waldfogel (2016): "Preference Externalities and the Rise of China: Measuring their Impact on Consumers and Producers in Global Film Markets," working paper.

Filson, D., and J. H. Havlicek (2018): "The Performance of Global Film Franchise: Installment Effects and Extension Decisions," *Journal of Cultural Economics*, 42, 447–467.

Filson, D., D. Switzer, and P. Besocke (2005): "At the Movies: The Economics of Exhibition Contracts," *Economic Inquiry*, 43(2), 354–369.

Francois, P., and T. van Ypersele (2002): "On the Protection of Cultural Goods," *Journal of International Economics*, 56, 359–369.

Hanson, G. H., and C. Xiang (2008): "International Trade in Motion Picture Services," Working Paper.

——— (2011): "Trade Barriers and Trade Flows with Product Heterogeneity: An Application to US Motion Picture Exports," *Journal of International Economics*, 83(1), 14–26.

Hausman, J. A., G. Leonard, and J. D. Zona (1994): "Competitive Analysis with Differentiated Products," *Annales d'Economie et de Statistique*, 34, 159–180.

Hennig-Thurau, T., V. Henning, H. Sattler, F. Eggers, and M. B. Houston (2007): "The Last Picture Show? Timing and Order of Movie Distribution Channels," *Journal of Marketing*, 71(4), 63–83.

Hennig-Thurau, T., M. B. Houston, and T. Heitjans (2009): "Conceptualizing and Measuring the Monetary Value of Brand Extensions: The Case of Motion Pictures," *Journal of Marketing*, 73(6), 167–183.

Hennig-Thurau, T., M. B. Houston, and G. Walsh (2006): "The Differing Roles of Success Drivers Across Sequential Channels: An Application to the Motion Picture Industry," *Journal of the Academy of Marketing Science*, 34(4), 559–575.

Hermosilla, M., F. Gutierrez-Navratil, and J. Prieto-Rodriguez (2018): "Can Emerging Markets Tilt Global Product Design? Impacts of Chinese Colorism on Hollywood Castings," *Marketing Science*, 37(3), 356–381.

Ho, C.-Y., M. Rysman, and Y. Wang (2019): "Demand for Performance Goods: Import Quotas in the Chinese Movie Market," Unpublished.

Holloway, I. R. (2017): "Learning via Sequential Market Entry: Evidence from International Releases of U.S. Movies," *Journal of International Economics*, 104, 104–121.

Luo, H. (2014): "When to Sell Your Idea: Theory and Evidence from the Movie Industry," *Management Science*, 60(12), 3067–3086.

Marvasti, A., and E. R. Canterbery (2005): "Cultural and Other Barriers to Motion Pictures Trade," *Economic Inquiry*, 43(1), 39–54.

McCalman, P. (2005): "International Diffusion and Intellectual Property Rights: An Empirical Analysis," *Journal of International Economics*, 67(2), 353–372.

Melitz, M. J. (2003): "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71(6), 1695–1725.

Moul, C. (2007): "Measuring Word-of-Mouths Impact on Theatrical Movie Admissions," *Journal of Economics and Management Strategy*, 16(2), 859–92.

Prasad, A., B. Bronnenberg, and V. Mahajan (2004): "Product Entry Timing in Dual Distribution Channels: The Case of the Movie Industry," *Review of Marketing Science*, 2, 1–18.

Sood, S., and X. Drèze (2006): "Brand Extensions of Experiental Goods: Movie Sequel Evaluations," *Journal of Consumer Research*, 33(3), 352–360.

Walls, W. D. (2009): "Screen Wars, Star Wars, and Sequels: Nonparametric Reanalysis of Movie Profitability," *Empirical Economics*, 37(2), 447–461.

Appendix - Not for Publication

Derivation of Budget Elasticity

Market share of a movie in country c is defined as

$$s_{jc} = \frac{\exp\left(\frac{\delta_{jc}+\alpha p_c}{1-\sigma}\right)}{D_c^\sigma + D_c}$$

where $D_c = \sum_{k \in J_c} \exp\left(\frac{\delta_{jc}+\alpha p_c}{1-\sigma}\right)$. The within-industry market share is

$$z_{jc} = \frac{\exp\left(\frac{\delta_{jc}+\alpha p_c}{1-\sigma}\right)}{D_c}.$$

Therefore, the budget elasticity is

$$\begin{aligned}
\eta_{jc} &= \frac{ds_{jc}}{dB_j}\frac{B_j}{s_{jc}} = \frac{\partial s_{jc}}{\partial \delta_{jc}}\frac{\partial \delta_{jc}}{\partial B_j}\frac{B_j}{s_{jc}} \\
&= \left(\frac{\frac{1}{1-\sigma}\exp\left(\frac{\delta_{jc}+\alpha p_c}{1-\sigma}\right)}{D_c^\sigma + D_c} - \frac{\frac{1}{1-\sigma}(\sigma D_c^{\sigma-1}+1)\exp\left(\frac{\delta_{jc}+\alpha p_c}{1-\sigma}\right)^2}{(D_c^\sigma + D_c)^2} \right) \cdot \frac{\partial \delta_{jc}}{\partial B_j}\frac{B_j}{s_{jc}} \\
&= \frac{1}{1-\sigma} s_{jc}(1-(\sigma D_c^{\sigma-1}+1)s_{jc}) \cdot (\gamma_2 + \gamma_3 \cdot \text{Action}_j)/B_j \cdot \frac{B_j}{s_{jc}} \\
&= \frac{1}{1-\sigma}(1-(\sigma D_c^{\sigma-1}+1)s_{jc}) \cdot (\gamma_2 + \gamma_3 \cdot \text{Action}_j) \\
&= \frac{1}{1-\sigma}(1-(\sigma D_c^{\sigma}+\sigma D_c)s_{jc}/D_c - (1-\sigma)s_{jc}) \cdot (\gamma_2 + \gamma_3 \cdot \text{Action}_j) \\
&= \frac{1-\sigma z_{jc} - (1-\sigma)s_{jc}}{1-\sigma} \cdot (\gamma_2 + \gamma_3 \cdot \text{Action}_j)
\end{aligned}$$

where $\text{Action}_j = 1$ if Movie j is an Action movie, and $\text{Action}_j = 0$ if it is a Non-Action movie. For the same ticket price and movie quality, two movies have the same within market share z_{jc} and overall market share s_{jc}. In this case, an Action movie has a higher budget elasticity than a Non-Action movie if $\gamma_3 > 0$.

Table A1: Export Regions and Countries

Region	Country
Asia	China, Hong Kong, Japan, Malaysia, The Philippines, Singapore, South Korea, Thailand
Eastern Europe	Bulgaria, Poland, Russia, Serbia, Slovakia, Slovenia, Ukraine, Croatia, Czech Republic, Hungary, Romania, Turkey
Western Europe	Australia, Austria, Belgium, France, Greece, Germany, Italy, the Netherlands, Spain, the United Kingdom, Denmark, Finland, Iceland, Norway, Sweden
South America	Argentina, Brazil, Colombia, Chile, Peru, Venezuela, Mexico, Uruguay

Note: Some countries do not fall squarely in the geographic boundary of the associated region, such as Australia. We group the countries using both the geographic and cultural closeness of the countries in each "region".

Table A2: Quality Production Function Estimates - Alternative IV for Budget

		Asia	E. Europe	W. Europe	S. America	U.S.
Action	(γ_{1r})	-2.216***	-1.031**	-3.447***	-5.336***	-0.601
		(0.665)	(0.474)	(1.031)	(1.551)	(1.871)
ln(Budget)	(γ_{2r})	0.222***	0.219***	0.194***	0.250***	0.287***
		(0.019)	(0.012)	(0.012)	(0.018)	(0.020)
Action× ln(Budget)	(γ_{3r})	0.223***	0.084***	0.190***	0.291***	0.023
		(0.037)	(0.026)	(0.057)	(0.085)	(0.103)

Notes: We estimate the model using an alternative instrumental variable - movie studios' numbers of wide-released movies from the previous year. Table A2 presents the estimated model coefficients. All estimates control for country fixed effects and a time trend, as well as unobserved quality shocks $\hat{\nu}_1$ and $\hat{\nu}_2$. Because US entries are assumed to be 100%. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A3: Mean Budget Elasticity - Alternative IV for Budget

	Asia	E. Europe	W. Europe	S. America	U.S.
Action	1.76	1.22	1.55	2.17	1.23
Non-Action	0.91	0.85	0.79	1.02	1.10
$\frac{\eta_{Action}}{\eta_{Non-Action}}$	1.92	1.44	1.95	2.13	1.12

Notes: We estimate the model using an alternative instrumental variable - movie studios' numbers of wide-released movies from the previous year. Table A3 shows the corresponding average budget elasticities across genres and regions.

Table A4: Mean Budget Elasticity Across Regions - Holding Budgets Fixed

	Asia	E. Europe	W. Europe	S. America	U.S.
Action	1.05	0.87	1.14	1.28	1.23
Action, $\gamma'_{3r} = 0$	0.48	0.54	0.57	0.41	1.09
Non-Action, $\gamma'_{2r} = \gamma_{2r} + \gamma_{3r}$	1.08	0.88	1.16	1.30	1.25
Non-Action	0.49	0.54	0.58	0.42	1.10

Notes: The first row reports the weight mean budget elasticities of Action movies across regions. The second row reports the weight mean budget elasticities of the same movies, if they become Non-action movies, in other words, $\gamma'_{3r} = 0$. The fourth row reports the weight mean budget elasticities of Non-action movies across regions. The third row reports the weight mean budget elasticities of the same movies, if they become Action movies, in other words, $\gamma'_{2r} = \gamma_{2r} + \gamma_{3r}$.

Table A5: Movie's Dialogue with Different Exposure in Global Market

Region	Movies that Export to	
	$<$ 1/2 of the countries in the region	$\geq$ 1/2 of the countries in the region
Asia	11,854	10,104
	(6,666)	(5,042)
Eastern Europe	11,101	10,423
	(5,776)	(5,505)
South America	11,098	10,456
	(5,749)	(5,526)

Notes: The table shows average number of words in a movie for movies with different exposure in different regions. Standard deviations in parentheses.

Table A6: Quality Production Function Estimates - Model Directly Fitting δ_{jc}

		Asia	E. Europe	W. Europe	S. America	U.S.
Action	(γ_{1r})	-0.452	-0.211	-2.670***	-2.952***	-0.801
		(0.665)	(0.474)	(0.453)	(0.684)	(0.821)
ln(Budget)	(γ_{2r})	0.316***	0.200***	0.186***	0.248***	0.269***
		(0.019)	(0.013)	(0.012)	(0.017)	(0.019)
Action× ln(Budget)	(γ_{3r})	0.022	0.011	0.148***	0.159***	0.035
		(0.037)	(0.026)	(0.025)	(0.038)	(0.045)

Notes: All estimates control for country fixed effects and a time trend, as well as unobserved quality shocks $\hat{\nu}_1$ and $\hat{\nu}_2$. Because US entries are assumed to be 100%, we use the same US parameter estimates as in the benchmark model. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A7: Goodness of Fit - Model Directly Fitting δ_{jc}

		Asia	E. Europe	W. Europe	S. America	U.S.
Within Market Share						
Action	Data	62.0%	43.2%	41.7%	45.4%	37.2%
High-Quality	Model	41.4%	34.6%	47.4%	50.3%	37.6%
Action	Data	19.0%	22.5%	19.3%	19.2%	15.9%
Low-Quality	Model	18.4%	19.0%	16.5%	14.5%	17.5%
Non-Action	Data	15.9%	26.7%	28.3%	25.7%	32.0%
High-Quality	Model	33.9%	35.1%	27.0%	28.3%	29.9%
Non-Action	Data	3.0%	7.6%	10.7%	9.7%	14.9%
Low-Quality	Model	6.2%	11.3%	9.1%	6.9%	15.0%
Ratio of Aggregate Box-office Revenues						
Model/Data		3.344	1.432	1.410	1.444	1.020
Average Export Probabilities						
Action	Data	93.2%	93.9%	94.3%	90.4%	100.0%
High-Quality	Model	94.7%	97.0%	99.6%	95.1%	100.0%
Action	Data	86.8%	90.1%	91.8%	89.8%	100.0%
Low-Quality	Model	91.2%	93.4%	96.9%	80.9%	100.0%
Non-Action	Data	59.7%	77.2%	83.2%	80.7%	100.0%
High-Quality	Model	90.6%	92.0%	96.6%	91.5%	100.0%
Non-Action	Data	35.6%	37.0%	37.7%	36.9%	100.0%
Low-Quality	Model	37.4%	38.3%	39.8%	37.3%	100.0%

Notes: Movie qualities are not directly observed, so movie budgets in data are used as a proxy for quality. "High-quality" means that a movie has an above-median budget within its genre and release year. "Low-quality" is similarly defined.

TABLE A8: Quality Production Function Estimates - Model without γ_{3r}

		Asia	E. Europe	W. Europe	S. America	U.S.
Action	(γ_{1r})	-0.064***	-0.022	-0.004	-0.084***	-0.166***
		(0.023)	(0.017)	(0.015)	(0.023)	(0.027)
ln(Budget)	(γ_{2r})	0.300***	0.202***	0.218***	0.282***	0.275***
		(0.010)	(0.011)	(0.010)	(0.015)	(0.017)
Action× ln(Budget)	(γ_{3r})	0	0	0	0	0
		-	-	-	-	-

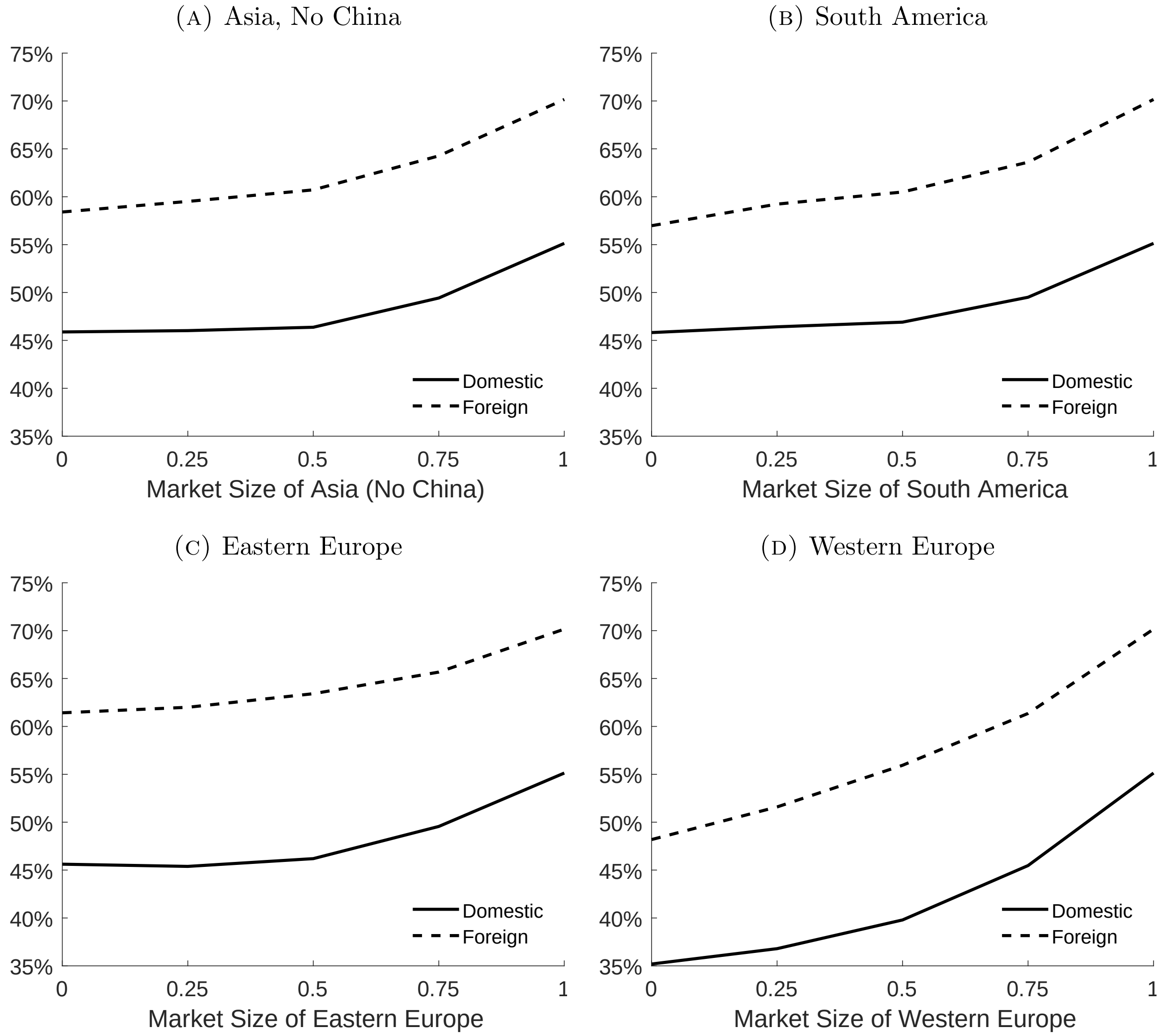
Notes: All estimates control for country fixed effects and a time trend, as well as unobserved quality shocks $\hat{\nu}_1$ and $\hat{\nu}_2$. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

TABLE A9: Goodness of Fit - Model without γ_{3r}

		Asia	E. Europe	W. Europe	S. America	U.S.
		Within Market Share				
Action	Data	62.0%	43.2%	41.7%	45.4%	37.2%
High-Quality	Model	63.1%	44.8%	42.0%	46.5%	37.2%
Action	Data	19.0%	22.5%	19.3%	19.2%	15.9%
Low-Quality	Model	16.6%	17.6%	18.1%	18.4%	17.6%
Non-Action	Data	15.9%	26.7%	28.3%	25.7%	32.0%
High-Quality	Model	13.8%	28.0%	30.4%	29.2%	30.1%
Non-Action	Data	3.0%	7.6%	10.7%	9.7%	14.9%
Low-Quality	Model	6.5%	9.6%	9.5%	6.0%	15.0%
		Ratio of Aggregate Box-office Revenues				
Model/Data		1.000	1.000	1.000	1.000	1.019
		Average Export Probabilities				
Action	Data	93.2%	93.9%	94.3%	90.4%	100.0%
High-Quality	Model	92.7%	94.8%	96.4%	96.3%	100.0%
Action	Data	86.8%	90.1%	91.8%	89.8%	100.0%
Low-Quality	Model	76.6%	81.8%	85.2%	81.9%	100.0%
Non-Action	Data	59.7%	77.2%	83.2%	80.7%	100.0%
High-Quality	Model	67.0%	86.7%	87.6%	90.8%	100.0%
Non-Action	Data	35.6%	37.0%	37.7%	36.9%	100.0%
Low-Quality	Model	31.4%	33.6%	37.0%	37.3%	100.0%

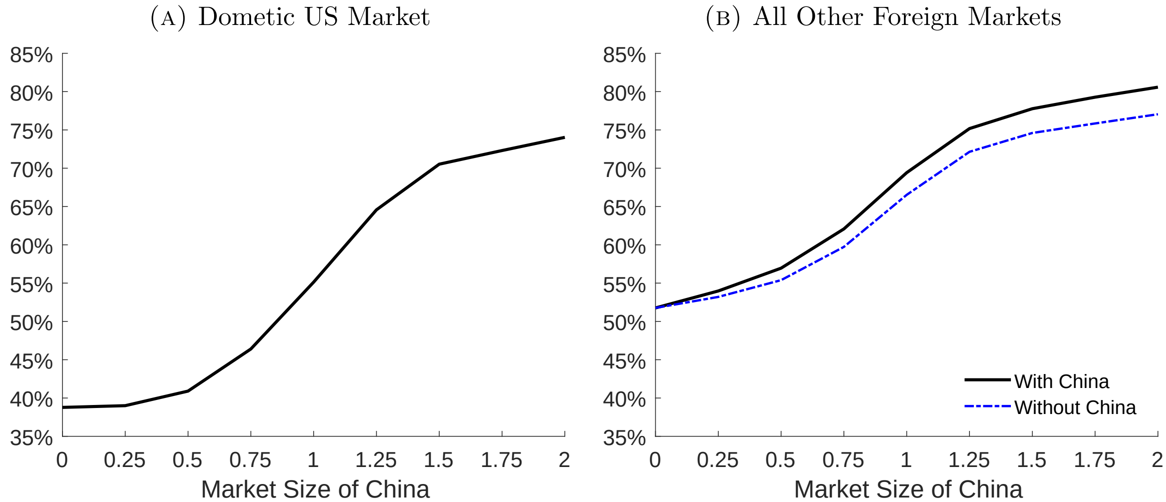
Notes: Movie qualities are not directly observed, so movie budgets in data are used as a proxy for quality. "High-quality" means that a movie has an above-median budget within its genre and release year. "Low-quality" is similarly defined.

Figure A1: Action Movie Market Share - Market Expansion by Region



Note: Figure A1 shows the Action movies' market share changes in both the US domestic market (solid lines) and foreign export markets (dashed lines) as market sizes expand in different regions. We do not make direct comparisons across regions because of the differences in baseline market sizes and country fixed effects. Based on Figure A1, we can conclude that significant market expansion in any regional markets, not just in China, would cause a rise of Action movies in Hollywood.

Figure A2: Action Movie Market Share of Box-office Revenue



Note: Figure A2 shows that Action movie market shares rise further as the Chinese market expands beyond its current size. We simulate the counterfactual worlds where the Chinese market size is 25, 50, 75, and 100 percent larger than the *Baseline* world. The Chinese market becomes a more important revenue source of Hollywood movies. The Chinese revenue share in the worldwide box-office would increase from 10.0 percent in the *Baseline* to 19.4 percent in the *Chine*$\times$*2* world. As a result, Action movies' domestic market share would increase from 55.1 percent to 74.0 percent, and the foreign market share would increase from 69.4 percent to 80.6 percent. Figure A2 also shows that the increases in Action movies' market shares are not linear. As the Chinese market size expands beyond its *Baseline* level, the rates of Action movie market share increases gradually become lower. The slower increases are due to the decreasing marginal return to budget investment when Action movies' perceived qualities become higher.