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Can Emerging Markets Tilt Global Product Design? Impacts of Chinese Colorism on Hollywood Castings

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Abstract. In various cultural and behavioral respects, emerging market consumers differ significantly from their counterparts of developed markets. They may thus derive consumption utility from different aspects of product meaning and functionality. Based on this premise, we investigate whether the economic rise of emerging markets may have begun to impact the typical one-size-fits-all design of many international product categories. Focusing on Hollywood films, and exploiting a recent relaxation of China's foreign film importation policy, we provide evidence suggesting that these impacts may exist and be nonnegligible. In particular, we show that the Chinese society's aesthetic preference for lighter skin can be linked to the more frequent casting of pale-skinned stars in films targeting the Chinese market. Implications for the design of international products are drawn.

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1. Introduction

Fast-paced, sustained GDP growth and increasing integration into world trade have made emerging markets important new players in the global economy. These economies have rapidly enlarged their middle classes and significantly reduced poverty (Sala-i Martin 2006, Sudhir et al. 2015, Chandy and Narasimhan 2015), endowing significant shares of their populations with purchasing power and access to retail commerce. As a result, this process has articulated an influx of “newly endowed” consumers into the global demand for products and services.

In this paper, we investigate the importance of this phenomenon for the design of international products. These newly endowed consumers are known to significantly differ from their counterparts of developed markets in cultural and behavioral respects (Henrich et al. 2010, Sheth 2011). For example, whereas the former emphasize embeddedness and hierarchy, the latter emphasize autonomy and egalitarianism (Burgess and Steenkamp 2006). Differences like these suggest that consumers from emerging markets may place utility value on different aspects of product meaning and functionality. Their activation into the global demand

for products and services may therefore bring along a shift in aggregate consumer preferences within the total addressable market, prompting an impact on product design.

Although these design impacts may unfold through additional product variety, they are likely to be more transparently observed on products that cannot be meaningfully customized to each international market. That is, on products that, because of the nature of their development process, are “condemned” to a largely standardized design. These products are the focus of this study. For ease of reference, we call them “global products.” We associate them with categories such as feature films, TV series, music, video games, literature, and other commercial art forms, as well as alternative kinds of written and audiovisual media (e.g., blogs, podcasts). We observe that, despite the fact that some of these may undergo minor forms of international customization, large fixed redesign costs prevent deep customization. For example, although feature films may be dubbed and slightly edited when released in a foreign market, the more important determinants of their appeal to audiences (aesthetics, storyline, central themes, starring actors) are deeply enmeshed in,

and inextricably tied to, their core structures, and thus largely uncustomizable. We ask, Can the newly acquired importance of emerging markets impact their one-size-fits-all design?

To shed light on this question, we study the design of Hollywood films. Described as unique and complex artifacts (Craig et al. 2005), feature films embody “explicit visions of the world” (Moul 2005, p. 18), and are “rich in cultural meaning” (Craig et al. 2005, p. 81). They thus entail a likely arena for a shift of aggregate cultural preferences to manifest on.¹ Our research design is also informed by the graduality of emerging markets’ rise to prominence—a process that has unfolded over the past three decades. Because other relevant factors have also been changing during this period, isolating the referenced preference shift over such a long time span would be difficult. We therefore exploit the variation created by a single event, which heightened the global relevance of consumer preferences from a leading emerging market; the 2012 relaxation of China’s foreign film importation policy.

Since the Cultural Revolution, China has maintained stringent restrictions on foreign film importation. These started to be challenged by the U.S. Government when China joined the World Trade Organization (WTO) in 2001. During this period, however, there was a large amount of uncertainty regarding whether, when, and how China would respond. Fostered by the broader political circumstances, these restrictions were finally loosened in February 2012. From the perspective of Hollywood studios, this policy change effectively constituted a one-time, discontinuous, and large increase in the importance of Chinese preferences within the total addressable market. Our empirical analysis aims at deciphering whether, in adapting to the new market environment, Hollywood studios *accommodated* core cultural elements of film design to elements of the Chinese culture.

By 2012, Hollywood was already actively pursuing the booming Chinese theatrical market.² Anecdotal evidence suggests that this push may have impacted film design through the inclusion of additional footage, and the implementation of storylines exalting Chinese people, values, or institutions.³ While noteworthy, these events were reportedly rare. More importantly, they may not necessarily constitute evidence of accommodation to the culture of Chinese people. The inclusion of Chinese-targeted additional footage (a mild form of customization) may have been motivated by the very goal of avoiding to accommodate the otherwise standard design. In turn, the implementation of storylines that exalt Chinese themes may have been solely oriented at earning the goodwill of the regulating authority (and with it, market entry). These themes would thus reflect accommodation to the preferences of gatekeepers rather than to those of audiences. With

these caveats in mind, we examine a marker of cultural accommodation that is both deeply ingrained in a film’s design, while at the same time not a suspected object of scrutiny by Chinese gatekeeping authorities. That marker is the skin color of starring actors.

Evidence from a variety of domains converges on the notion that people in China (and other Asian societies) exhibit a strong form of *coloristic preferences*, by which pale skin is aesthetically preferred to dark. These preferences were forged over 2,000 years ago in the Chinese society. Today, they do not appear to be a purely implicit cultural trait, nor a matter of public controversy. Our review further suggests that coloristic preferences in China manifest more as a “light-skin premium” than a “dark-skin penalty,” and that skin tone corresponds to central axis for perceived beauty, particularly for women. As such, skin color plays a defining role in the burgeoning Chinese cosmetics market. To this point, an official of China’s cosmetics trade association stated that “skin whitening has a long history in Asia [. . .] this obsession with whiteness has not faded over time” (Xi 2011).⁴

Our empirical strategy exploits an important feature of observed patterns of U.S. film entry into the Chinese market; that is, films that enter tend to have a rather specific profile, which did not materially change after the new policy came into place. Based on this observation, and using a rich set of observable design characteristics, we are able to rank films in terms of their exposure to the policy shock. For example, because low-budget, 2D, horror, or comedy films rarely enter China, it can be presumed that their castings were less impacted by the policy change than that of high-budget, 3D, action films, which enter the market much more frequently. We draw inference from a differences-in-differences (DiD) specification, which implements a comparison between films produced before and after the policy change, across the range of exposure to the shock.

The leading threat to causal inference is the potentially endogenous nature of film design and production.⁵ Following the policy change, studios may have redirected their innovation towards China, by favoring specific genres, formats, or storylines, or by engaging in production and commercial arrangements that improve the prospects of entry into this market. Although these effects may not all be inconsistent with cultural accommodation, they would bias our estimates. Yet we find no evidence to support them. In particular, we do not observe a “China redirection” in the distribution of predicted entry probabilities, nor signs of systematic changes in the types of storylines developed by highly exposed films. That is, these results suggest that the policy change did not intensify Hollywood’s pursuit of the Chinese market, as reflected by these variables. Note that, because our data may not

capture all relevant design and production features, it is still possible that our estimates are afflicted by a bias introduced through these means. However, results of a series of robustness and falsification tests suggest that, if present, this bias should be minor, and unlikely to drive our conclusions.

According to our preferred specification, the participation of pale-skinned star actors among films in the top decile of shock exposure increased by about 8% as a result of the policy change. We take this result as evidence of cultural accommodation, and refer to it as the *light-skin shift* (LSS). Furthermore, consistent with the idea that Chinese coloristic preferences impose more stringent beauty standards on women, and better resemble a “light-skin premium” than a “dark-skin penalty,” we find that the LSS mainly operated through the more frequent inclusion of pale-skin actresses, and that it was not associated with a sharp decrease in the participation of actors of dark-most skin colors.

We confront our main finding against a leading alternative hypothesis. This is, the possibility that the LSS was articulated by a shift toward more popular actors (or *superstars*), but who happen to be pale skinned.⁶ Had the LSS been driven by such an effect, we would not observe it when dropping superstars from the sample. We nevertheless continue to observe it. This is the case both when an actor’s superstar status is determined by a proxy for worldwide popularity, or by one for their popularity in China. Thus, the LSS does not seem to have been driven by a *superstar shift*. Last, we investigate whether the LSS may have been rooted on the behavior of Chinese gatekeeping authorities. Results suggest that this was not the case.

Although emerging markets have received growing amounts of interest from marketing scholars, the vast majority of this work has treated them as “testing grounds” for theories coined in the context of developed markets, or focused on understanding the nature and local implications of their institutional, cultural, and behavioral differences with developed markets (Burgess and Steenkamp 2013, Narasimhan et al. 2015, Sudhir et al. 2015, Chandy and Narasimhan 2015). We contribute to this agenda by highlighting that these differences may also have first-order implications on a global scale. The culturally sensitive nature of our dependent variable further reinforces this point, by suggesting that the emerging markets’ newly acquired economic prowess may be propelling their consumers’ preferences to “swim against the tide” on the global stage. Our work also contributes to the literature on product design, where large-scale empirical studies are scant (Bloch 1995, Luchs and Swan 2011).

Our results have an obvious implication for the design of international products and services. Whereas analyzing the cultural and behavioral landscape of developed economies may have been sufficient to inform

design in the past, the irruption of emerging markets renders it likely insufficient now. Moreover, in several ways, the irruption of emerging markets has added preference heterogeneity to the global addressable market, possibly increasing the difficulty of achieving satisfactory one-size-fits-all designs. This challenge stands out in the context of feature films, where consumption value is assessed through the lens of culture, and where wide cultural divides may force studios to reconcile somewhat opposing views. Such difficulties resonate, for example, with the case of “The Great Wall” (2016), whose lackluster commercial performance was rationalized on the basis that “the film pulled itself in two directions to please the ‘other’ audience, which in the end pleased neither side of the world” (Mendelson 2017a).⁷ Although we focus here on coloristic preferences, such cultural divides may also manifest with respect to other culturally sensitive issues, such as women’s rights, the scope of personal liberties, and the respect for authority. Storylines and themes that shy away from such polarizing topics, or which avoid stinging representations thereof, may help studios avoid these unwanted trade-offs.

Although our results connect with the recent controversy about racism in Hollywood (Kang et al. 2014) at a high level, when examined carefully, such a connection is tenuous at best. We thus ask the reader to interpret this with extreme care. As we explain in Section 2, colorism does not equate to racism. There may be significant variation in skin tones within races, and colorism may manifest within individuals of the same race. More importantly, the leading form of racism discussed in the United States is usually framed as a systematic prejudice or discrimination against black individuals. Our results do not evidence this effect. Instead, our results sketch a favoritism effect for individuals of pale-most skin tones. This effect seems to have been sustained by the lower participation of actors of all darker skin tones. Besides African-American actors, these darker skin tones also include actors that appear to have Latino, Indian, and Asian ethnicities, as well as many relatively darker-skinned Caucasians, such as Adam Sandler and Al Pacino.

2. Coloristic Preferences

Coloristic preferences operate over the skin color of people, such that lighter skin is preferred to darker (Hunter 2013).⁸ The manifestation of these preferences—*colorism*—does not equate to racism. Colorism is a matter of skin tone, which means that it can manifest within or across races (Hunter 2013). Furthermore, unlike racism, colorism is not strongly linked to manifestations of violence or repression.

Colorism is also present in the Western world, including the United States (Hunter 2007). For these

societies, however, factors such as the more pervasive racial heterogeneity among the population and in the media, and the vigorous affirmative action against racial disparity issues, suggest that overt coloristic manifestations may be met with social disapproval, and that coloristic preferences may not shape beauty standards as strongly as in China.

According to Dikötter (1992), the Chinese society developed a white-black polarity over 2,000 years ago, before the Qin dynasty. As in Europe before the industrial revolution, light skin became a signaling device for class status, differentiating a leisure class elite from lower-class groups. Mostly comprised of the agricultural peasantry, these tended to have darker skin tone because of their more intense exposure to sunlight because of outdoor labor.

Symbolized by the use of “white jade” as a metaphor for a light complexion (Dikötter 1992),⁹ fair skin became idealized and associated with intellectual endeavor, beauty, elegance, and virtue (Sautman 1994). This symbolism permeated into beauty standards, as is reflected by one point in the *Ten Commandments of Classical Beauty of Ancient China*—a woman’s beauty follows from “slender waists and snow-white skin” (细腰雪)—, and the proverb “One whiteness covers up one hundred ugliness” (Sim 2012).

While the mechanics of skin color differentiation were disrupted in Europe by the Industrial Revolution, they remained largely intact in China, which continued to rely on an agricultural economy until the economic reforms of 1978 gave way to industrialization (Yao 2000). In Europe, the Industrial Revolution caused the migration of outdoor to indoor labor (Azoulay et al. 2009), and the massification of steam-based transportation technology prompted elites to vacation in warm and sunny locations. Furthermore, relative to the Western world, China has maintained a high degree of ethnic and cultural homogeneity, even throughout its recent process of economic development and global integration (The Economist 2016).¹⁰

Observers of the Chinese society rely on this history to explain how skin color, identity, and social status connect in today’s China. Referencing Hong Kong as a proxy for mainland Chinese society, Leong (2006, p. 167) states that “skin colour operates as a visual agent in defining the boundaries of cultural identity, and in identifying a person’s place in a local social hierarchy,” and suggests that white skin is the most important element of personal beauty, as well as a marker for good health. Sautman (1994, p. 427) reaffirms the role of pale skin as a defining trait of beauty standards in today’s China: “fair skin continues to be a standard of female beauty. Many urban Chinese women take pains to avoid the sun and some use whitening creams.”

These marked coloristic preferences can be linked to a defining feature of the cosmetics market in China and

other Asian countries. For example, the China director of the cosmetics multinational L’Oréal Paris has stated that “(Asian) women at every age want to bleach their skin [. . .] Since fairness is the specific requirement of Asian women, these kinds of products are only available in this area. But we do believe skin whitening will retain its very important position here” (Xi 2011). Correspondingly, Asia has been the fastest-growing region in the global skin-lightening market since the 1970s (Tan 2012), exhibiting rates of growth in excess of 70% in recent years (Xi 2011). Skin-whitening products now account for about 30% of the over US\$5 billion-a-year skin care Chinese market, making it its largest category (Xi 2011). By comparison, this share is less than 3% in the United States (Statista 2017). The strength of the phenomenon is also reflected by intense competition and innovation in the category (Tan 2012), as well as by graphic advertisement campaigns that overtly associate departures of pale skin with ugliness and awkwardness (Xi 2011).

A common thread across these references is the idealization of white skin as opposed to the denigration of black skin. This aspect may be rooted on the mechanics of social differentiation, as they apply to the Chinese context. In particular, because the genetically determined skin colors of Chinese people are generally light within the broad spectrum of skin colors in humans (Wei et al. 2007), black skin is a virtually irrelevant point of reference, and thus an ineffective anchor to base differentiation on. This suggests that coloristic differentiation in China is likely to be driven by the degree of proximity to the “snow-white” ideal, rather than by the degree of separation from black skin extreme, as most Chinese people would be roughly equally apart from it.¹¹ The common practice of avoiding sun exposure (Levin 2012) supports this view, as it suggests that even minor distortions to a pale skin tone can jeopardize this ideal. We conceptualize this idea by saying that coloristic preferences in China manifest more like a “light-skin premium” than a “dark-skin penalty.”

We conclude with two examples suggesting that Chinese colorism may influence consumption decisions in areas beyond beauty products. In the early days of the modern Chinese photography market, Fuji outperformed Kodak. Smith (1996) suggested that the cause was partly rooted on the former’s products’ skin-lightening effect. Kodak later replicated this feature. The popularity of recent “selfie-enhancing” cameras and apps—known to produce the same effect—attests to the same point.¹² Chinese coloristic preferences could also be linked to the recent controversy sparked by the poster of “Star Wars: The Force Awakens” (2015). The controversy arose because, relative to the poster’s U.S. version, the Chinese version visibly minimized the character played by the black actor Jon Boyega, while at the same time highlighted those played by the white

actress Carrie Fisher and the white actor Harrison Ford (Child 2015).

3. Regulatory Framework

3.1. China's Foreign Film Importation Policy

After a long ban established during the Cultural Revolution, the importation of foreign films was reinstated in China in 1994, although with strict regulations. The purpose of these regulations was twofold. The first was to support the domestic film industry by protecting it from international competition (O'Connor and Armstrong 2015). The second, to control the flow of information and content that may undermine the values espoused by the Chinese Communist Party (CCP), or which portrayed the country or its people in a negative light (O'Connor and Armstrong 2015).¹³ To this day, all films that enter China may be censored, or required, to alter some of its content.

Since 1994, there have been two main modes for foreign films to enter the Chinese market. These are "revenue share" and "flat-fee entry." Revenue sharing has been the predominant choice for large-budget Hollywood blockbusters, as it allows studios to participate in the box-office upside. In particular, studios retain about 13% of box-office revenues (Cieply 2012). Distribution is managed by a Chinese state-owned distributor (O'Connor and Armstrong 2015). Between 1994 and 2001, 10 films were allowed to enter in this mode. When China joined the WTO in 2001, this quota increased to 20. On the other hand, under the flat-fee model, studios receive a fixed upfront payment, but do not participate in box-office receipts. For this reason, flat-fee entry has traditionally been preferred by independent films or smaller productions.¹⁴

Although different State organisms may influence importation and censorship outcomes, the primary gatekeeping authority is the State Administration of Press, Publication, Radio, Film, and Television (SARFT). Because state-owned enterprises directly benefit from the importation of popular films, importation and content control decisions balance economic and ideological factors (Squire 2004),¹⁵ suggesting that a film's popularity among audiences may be a precondition for entry into the market. If satisfied, censorship and editing may be used to veto/modify those films that conflict with the gatekeeper's ideological mandate. Alternatively, films with weaker popular appeal may be favored if they align with it.

Content that exalts the Chinese culture, institutions, people, or values is expected to earn the SARFT's goodwill.¹⁶ However, it is not always clear what kind of content will achieve this goal or, in contrast, estrange the authority. For instance, when the animated film "Despicable Me 2" (2013) was denied entry, many suggested the reason was an alleged similarity between the animated characters ("minions") and the former

CCP's Secretary General Jiang Zemin, despite the authority's official position that the result was due to low profitability expectations (Child 2017). Qin (2011) and Grimm (2015) describe the convoluted organizational structure that is responsible for importation and censorship decisions (which includes a number of other organisms besides SARFT), suggesting that the resulting lack of transparency may be a deliberate feature, aimed at providing authorities "with the maximum level of flexibility and efficacy desired" in controlling informational flows (Qin 2011, p. 2).

3.2. 2012 Policy Change

Although the revenue-share quota was increased from 10 to 20 when China joined the WTO in 2001, the stringent restrictions continued to stand in contradiction with a WTO's central mandate. Namely, they breached the equal right of all enterprises and individuals—local and foreign—to import and distribute goods.

China was then called to eliminate these restrictions altogether. In open contradiction with its plans, China ignored the request, prompting the U.S. government to bring a case against it at the WTO (Voon 2009). Lacking a response, the case proceeded. In 2009 a WTO panel officially determined that China remained in violation of its obligations as a member of the organization (Voon 2009). The panel later rejected a Chinese appeal, and a formal call to comply was issued in March 2011 (O'Connor and Armstrong 2015).

Despite this sustained pressure, China's strong views on safeguarding its tight control over informational flows and protecting the domestic industry introduced a large amount of uncertainty regarding whether, when, and under what terms restrictions would be relaxed.

The new policy was forged during a February 2012 visit of then president-in-waiting Xi Jinping to the United States. Optimism for progress in film trade policy was weak at the time as, in an essay published earlier in 2012, then president Hu Jintao had laid out hostile views toward the cultural influence of the West, and its attempts to interfere with China's path (Wong 2012). Furthermore, although Hollywood's interests were not absent from the agenda, the focus was placed on bigger-picture issues, such as Human Rights violations, the Syrian crisis, the protection of intellectual rights, and "fair play" in technological trade (Lander and Wong 2012).

Nevertheless, policy reform was agreed on during the visit. It was struck before dinner on the last day of the visit, after Chinese agencies had signed off to the conditions earlier that day (Waxman 2012). The new policy was implemented later in 2012, and conceived as a five-year transitory framework until a more definitive set of rules was worked out.

This deal—known as the *Memorandum of Understanding* or *Xi-Biden* agreement—changed the conditions

for the most sought-after entry mode by large Hollywood studios, revenue sharing. Importation restrictions were relaxed in two main ways (Cieply 2012). The first was an increase in the percentage of box-office receipts retained by foreign studios, which rose from 13% to 25%. The second was an increase of the importation quota, which rose from 20 to 34. Although the policy reserved the 14 additional slots for 3D or IMAX films, there were no stated limits on 2D films among the remaining slots. Thus, to the extent that the supply of 3D/IMAX films would not meet Chinese demand, the policy change also improved entry prospects for 2D films. Both these changes point to an increased relevance of Chinese audiences' preferences from the perspective of Hollywood studios.

Despite not receiving much coverage from the Chinese media, some interpreted the memorandum as skillful political maneuvering by the impending President Xi: relative to the other issues at stake during the visit, the agreement constituted a relatively minor concession (Page 2012). Moreover, the larger number of U.S. films entering China would help to fill the rapidly expanding number of screens in China, and enable the transfer of technology to the domestic industry. For the White House, the agreement was perceived as a “well-timed victory,” at a time it verged on the “embarrassing collapse of legislation aimed at protecting intellectual property” (Waxman 2012). Finally, reflecting the reigning uncertainty and importance of the Chinese market for Hollywood studios, Motion Picture Association of America's (MPAA) Chris Dodd and Ron Kirk called the new agreement a “big deal” (Waxman 2012) and a “breakthrough” (Abrams 2012), respectively, while an analyst commented “the unthinkable happened” (Landreth 2012).

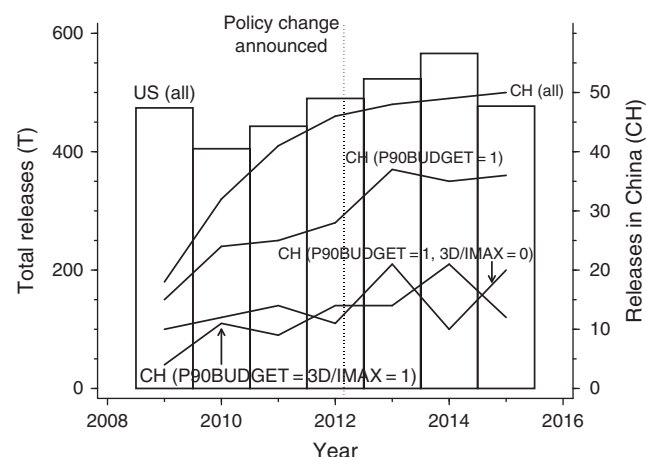
4. Data

The construction of our data set entailed two main parts: the retrieval of information for a sample of films from the IMDb website, and the codification of the skin colors of star actors included on each of these films. Details for each are provided in turn.

4.1. Films

We employed three criteria to select films. First, we focused on films released in the United States between 2009 and 2015, a time frame that provided us (at the time of data collection) with the roughly widest symmetric window around the policy change. Given our focus on the Hollywood industry, the second criterion was to select only those films for which the United States was listed among the origination countries. The large number of titles available from IMDb includes many small productions with little impact, so we further narrowed down the sample to the set of more impactful films. We implemented this refinement by

Figure 1. Number of Films: Sample Total (U.S.) and Releases in China (CH)



Notes. Total releases depicted by bars are computed based on films' U.S. release date. Releases in China are computed based on films' date of release in that market.

focusing on films with a large enough number of popularity votes on the IMDb website.¹⁷ The distribution across release years of the 3,378 films in the resulting sample is described by the bars in Figure 1. The number of released films is roughly stable across years.

We coded several design characteristics. Descriptive statistics are presented in Table 1. From technical specifications and keywords we generated the indicator 3D/IMAX, which identifies about 5% of films in our sample with these formats. IMDb data generally associates each film with more than one genre. Drama, thriller, and comedy are the more frequent ones.¹⁸ We also generated a set of sensitive content indicators (i.e., sex, nudity, violence, drug use, and strong language) by mining the keywords on the parental guide. About 68% of films include at least one such type of content.

Although these variables capture a good amount of variation regarding films' appeal to different audiences, their overall appeal may also be determined by other design features that are not fully controllable during production. One of these corresponds to the ratings awarded by the MPAA, which classify each film based on the suitability of their content to different audiences. These may add information by capturing higher-level design characteristics, which unfold through the specific portrayal of each type of content.¹⁹ Another non fully controllable variable corresponds to awards. Previous research has shown that the number of awards that a film is nominated to and wins may signal a film's quality to consumers.²⁰ We thus constructed the variables AWRNOM and AWRWON, which, respectively, track these.²¹

We also encoded production budgets. By a rational expectations argument, large budget films may be designed to have broad appeal, in a way that is not

Table 1. Sample Descriptive Statistics

	Mean	Std. dev.		Mean	Std. dev.
Genre indicators			Format indicator		
Action	0.19	0.39	3D/IMAX	0.05	0.21
Adventure	0.11	0.31	Production indicators		
Animation	0.03	0.18	USONLYFILM	0.77	0.42
Comedy	0.34	0.47	CHINESESTAR	0.00	0.07
Crime	0.14	0.35	CHINESECOPROD	0.01	0.12
Drama	0.48	0.50	BIG6STUDIO	0.37	0.48
Family	0.07	0.25	P75BUDGET	0.26	0.44
Fantasy	0.08	0.27	P90BUDGET	0.10	0.30
Horror	0.21	0.41	Major awards		
Mystery	0.10	0.30	AWRNOM	0.59	2.61
Romance	0.18	0.38	AWRWON	0.15	0.90
Science fiction	0.11	0.31	China entry indicator		
Thriller	0.34	0.47	CHINAENTRY	0.09	0.28
Other	0.11	0.31	Color coded star actors		
Sensitive content indicators			n_1	1.85	0.94
Sex	0.38	0.49	n_2	0.74	0.79
Nudity	0.16	0.37	n_3	0.11	0.37
Violence	0.35	0.48	n_4	0.11	0.37
Drug use	0.19	0.40	N (total)	2.83	0.43
Strong language	0.55	0.50			
MPAA rating indicators					
PG	0.07	0.26			
PG-13	0.21	0.40			
R	0.44	0.50			

captured by the above variables. This may occur, for example, through the inclusion of spectacular special effects or popular (high-earning) actors.²² In turn, Chinese authorities attempting to make efficient use of the small number of revenue-share slots may favor films that are both likely to appeal to a larger share of the population, and yield higher box-office receipts. Because budget information for about 45% of the films in the sample is missing from IMDb, we devised a coding scheme that primarily relies on identifying films at the top of the distribution. In particular, assuming that budget figures are more likely to be missing for films in which these are relatively small, we created the indicators P75BUDGET and P90BUDGET, which, respectively, activate for films whose budgets lie within the top 25% and 10% of the distribution of budgets for films released each year.²³

The indicator BIG6STUDIO was created to identify films involving at least one of the large “Big 6” studios.²⁴ About 37% of the films in the sample fall into this category. This variable may help us, among others, to control for potential differences stemming from studios’ experience engaging with Chinese authorities. Furthermore, we generated USONLYFILM to identify films produced by U.S. studios only. Because these films are produced in absence of international collaboration, they may have a relatively stronger emphasis on U.S. culture or values.

The variable CHINESECOPROD identifies coproductions with companies from China, which could

facilitate entry into that market.²⁵ Furthermore, to pick up the potential appeal derived from the inclusion of local actors, we retrieved each star actor’s country of birth. Because only a few of the stars in our data set are reported as born in mainland China, we also considered actors born in Hong Kong and Taiwan. The indicator CHINESESTAR identifies the small percentage (less than 1%) of films including at least one such actor.

Entry into the Chinese market is codified by the variable CHINAENTRY. An initial inspection of the data revealed that many of the films that IMDb reports as having been shown on Chinese screens do not correspond to standard commercial releases, but to limited releases (for example, in the context of screenings and festivals).²⁶ Because such releases may be subject to less stringent regulatory oversight, or mainly serve promotional goals, they are not accounted for by CHINAENTRY.

Patterns of entry into the Chinese market according to CHINAENTRY are depicted by the line plots of Figure 1. Whereas for bars (total releases of all U.S. films in our sample) the horizontal axis represents films’ release year in the United States, for line plots it represents the year of release in China. Thus, the relatively smaller numbers for 2009 likely stem from data censoring (as opposed to variations in the regulatory environment).²⁷

By focusing on the type of films that are more likely to enter through the revenue-share system (i.e., large budget films), the “CH(P90BUDGET = 1)” line maps out

the impacts of the new policy changes on entry quite closely. The observed number of this type of films that enters China is about 25 in 2010 and 2011, and a bit larger in 2012 (the new policy took effect during the summer of that year). The pattern exhibits a discontinuous increase in 2013, when a new level of about 35 is reached and maintained through the end of the sample period. The differences between the observed prepolicy and postpolicy change numbers with respect to the stated quotas of 20 and 34 may stem from coproduction arrangements, or flat-fee entry that we are not able to identify from the data at hand. However, these differences are small.

Note that, despite the new policy opening 14 new slots for 3D/IMAX films, the more immediate entry impact is registered among films without these formats. This supports our previous assertion that, despite its formulation, the new policy effectively expanded the market for both types of films during the covered period, 3D/IMAX and not. Last, we note that the difference between the total number of films (“CH(All)” line) and large-budget films that enter China (“CH(P90BUDGET = 1)” line) is likely to reflect the extent of flat-fee entry, that is associated with smaller budget productions. This difference suggests that only a very small fraction of small budget films (about 1% in our sample) will enter the market. Thus, for the latter, preferences of Chinese audiences are likely to be a much less important consideration for casting.

Finally, accounting for production lags will be important in our analysis. Film production requires a set of activities (casting, shooting, postproduction, etc.) which may take several months, or even years. This means that the impact of the 2012 policy change may have started to manifest among cohorts of films released in later years. To determine the specific cohorts that were impacted by the new policy, we retrieved production dates. In particular, we considered the date at which filming started, which was available for about 70% of the films in the sample. Using these dates to proxy for the time in which casting decisions were likely already defined, we computed the production lags. These correspond to the number of months between the reported date in which filming began, and the earliest release date in theaters. The distribution of these lags is presented in the online appendix. The median of this distribution is 17 months, which suggests that the new policy’s casting impacts must have been first perceived among the cohort of films released in 2014.

4.2. Skin Color Coding

We retrieved the list of actors starring in each film, and codified their skin color. We used the list of star actors presented on each film’s main IMDb profile. Beyond their on-screen relevance—that is, their importance as it relates to the number and types of scenes they participate in—star actors usually have an important role

in films’ promotional activities, thus representing the most culturally charged set of actors within the cast. A manual inspection of a number of films revealed that IMDb’s listed stars often correspond to those appearing in promotional posters, and that these lists tend to coincide with those of different Internet sources (Rotten Tomatoes, Wikipedia).²⁸

Discarding actors for whom there was no profile picture available from IMDb, this procedure resulted in a sample of 9,556 starring roles (i.e., actor/film combinations) and 4,728 actors. About 85% of the films in the sample have three stars, while a little under 2% have only one star. About 65% of the actors play only one role in the sample, while 15% play two. A relatively small fraction of actors (less than 5%) play more than 5 roles.

We codified the skin color of each actor using MTurk.²⁹ A profile picture of each actor was shown to five MTurk coders, asking each to rate the skin color in a scale with the following entries: “very light,” “light,” “medium,” “dark,” and “very dark.” We did not provide information about the actor’s filmography, nor anchored answers by providing examples. We then codified each response on a 1–5 scale, where 1 corresponded to very light and 5 corresponded to very dark, and averaged the scores awarded by coders within each actor. Figure 2 presents the resulting distribution. The median of this distribution is 2, which can be interpreted as 50% of actors having a skin color that is somewhere between very light and light.

To contextualize these results and assert their validity, we selected a random sample of actors across the range of skin color codes. Figure 3 presents the result. The most important feature of this figure is that it suggests that the MTurk coding results in a reasonably accurate ordering of actors based on their skin color: from left to right, skin colors progressively darken. The figure also suggests that the coding procedure was

Figure 2. Distribution of Color Codes Among the Sample of 4,728 Coded Starring Actors

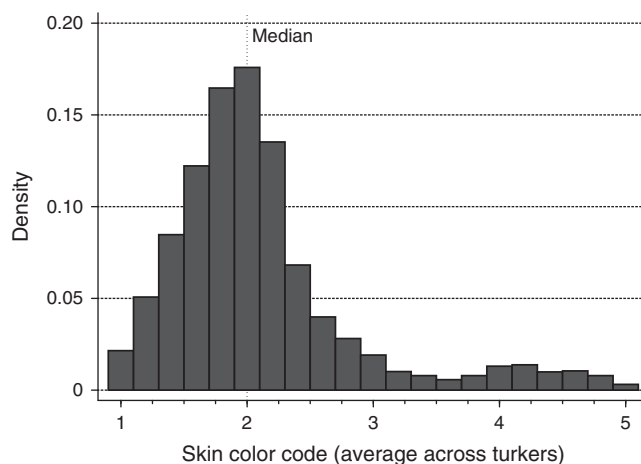
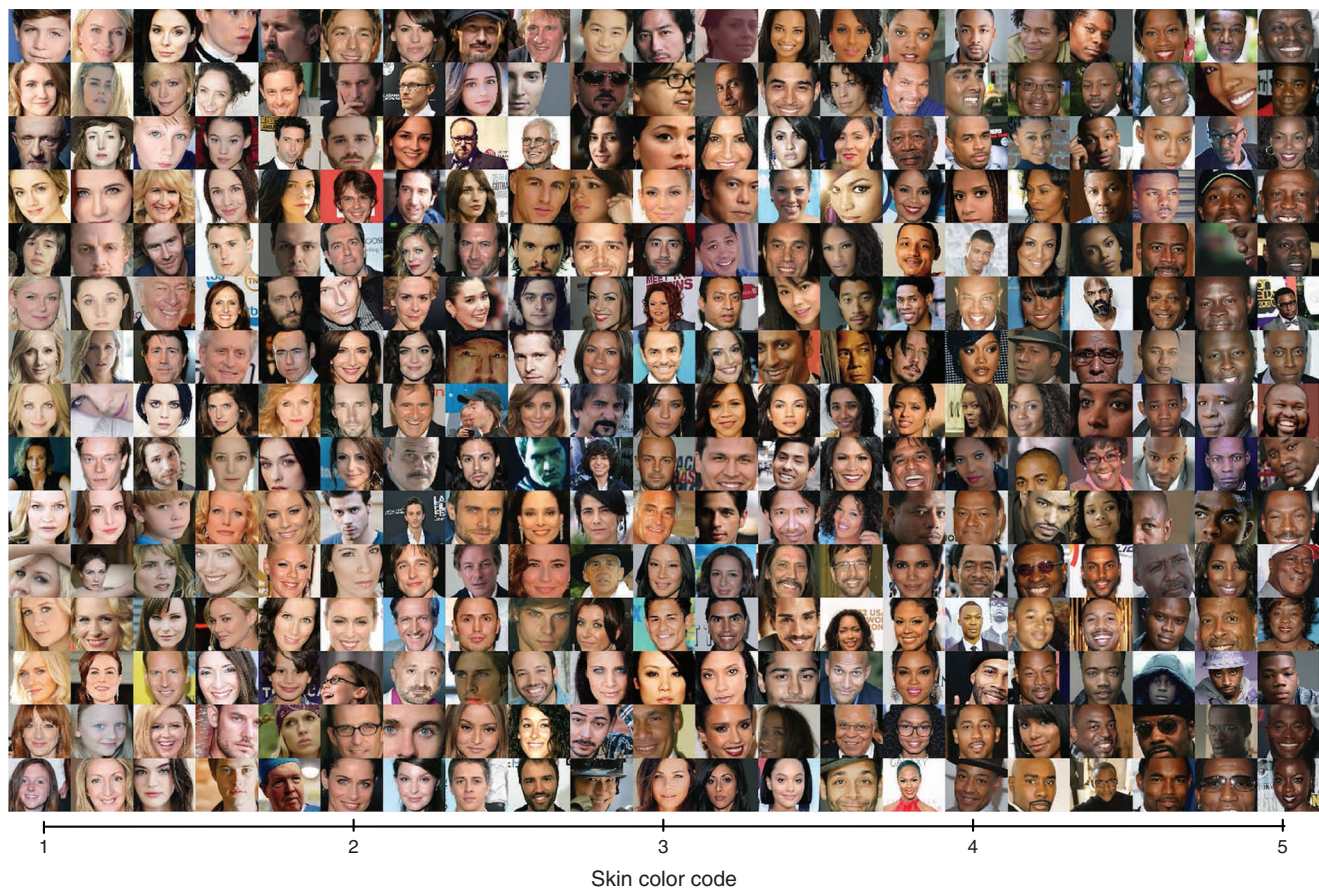


Figure 3. Random Sample of Actors and Actresses by Skin Color Code

Note. Images obtained from IMDb.

robust to less-than-ideal profile pictures. Pictures distorted by background light, or with actors wearing hats or hoods, do not evidence blatant coding errors.

To further assess the validity of this procedure, we investigated the degree of agreement among coders. We focused on within-actor coding discrepancies, computed as the difference between each coder's rating and the average across coders. Results point to low overall disagreement. The distribution is symmetric, over 75% of coder/actor ratings are within the $[-0.6, 0.6]$ interval, and 90% are within $[-0.8, 0.8]$. Furthermore, according to the criteria of Cicchetti (1994), the resulting value of 0.9 for the average absolute-agreement intraclass correlation is "excellent."

To facilitate the description of casting patterns across films, we translated the skin color alternatives presented to coders into a categorical variable. Denoting by c_a the average color score awarded to an actor a across coders, we assign the actor to a category $k = 1, \dots, 4$ if $k < c_a \leq k + 1$, with $k = 1$ for $c_a = 1$. We then constructed n_{ki} as the total number of actors that belong to category k and star in film i , and N_i as $\sum_k n_{ki}$. Thus, given the results of Figure 2, n_{1i} not only represents the number of actors in film i whose skin is

judged as light or lighter but also the number of actors who have lighter-than-median skin. These variables are summarized in Table 1. Because most films have three color-coded stars, the 1.85 average of n_{1i} suggests that two-thirds of actors fall in this category. The smaller average participation of dark-skinned actors ($k = 3, 4$) relative to their frequency in the distribution of Figure 2 stems from the smaller average number of roles played by them.

5. Empirical Strategy and Shock Exposure

5.1. Empirical Strategy

We conceptualize studios' production decisions through *product design pairs* (Y, X) , where Y corresponds to observed casting decisions, and X corresponds to the remaining film's design observables (e.g., genre, content, etc.). Within the latter we also include observable "behind the scenes" production arrangements (e.g., coproductions, budget, etc.). Consistent with our empirical analysis, we restrict our definition of Y to only encompass stars' skin colors, assuming their independence with respect to other characteristics of relevance (e.g., acting skills, experience).

The theoretical object of interest is the optimal casting policy, $Y^* | X$. We understand this as the criteria that guides optimal actor selection given a film's characteristics X . For example, films inspired on World Wars may call for light-skinned actors, as these events took place before major waves of African and Middle Eastern immigration into Europe. For these films, the strive for historical accuracy may lead to an "organic" or "natural" gravitation toward light-skinned stars.

To rationalize these policies, we denote by $\mathcal{P}(Y)$ the distribution of preferences for light-skinned stars in the total addressable (global) market. Once the policy change became effective, Chinese coloristic preferences acquired greater relevance within this market, inducing a shift in this distribution. We denote this shift by $\Delta\mathcal{P}(Y)$. Our inference is based on a comparison of optimal casting policies $E[Y^* | X]$ between films whose characteristics X suggest a relatively large shift $\Delta\mathcal{P}(Y)$, and others for which the shift was presumably smaller. Our focus on X -conditional casting policies means that we aim to identify a potential change in the set or criteria that govern the selection of stars.

We next present a framework that allows us to implement this strategy in a simple and transparent way. In this framework, $\Delta\mathcal{P}(Y)$ is operationalized through a "treatment intensity" function $\text{EXPOSURE}(X) \in [0, 1]$. This function is computed based on patterns of China entry observed prior to the policy change. We use three variants of EXPOSURE , one dichotomic and two continuous. The consistency of results obtained from each of these illustrates the robustness of our main finding.

Under certain assumptions, a DiD specification allows us to identify the causal impact of the policy change on optimal casting policies. At a broad level, the effect is identified by the progression of "pre/post" differences in $E[Y^* | X]$ along the support of EXPOSURE . Specification details and assumptions are addressed in Section 6. We investigate the validity of the required assumptions, devoting special attention to the potential endogeneity problem rooted on studios' ability to choose films' observable and nonobservable design characteristics.

Section 5.2 develops the basic elements needed to construct EXPOSURE . We employ probit specifications, which relate observables characteristics X to CHINAENTRY . As expected from our review of Section 3, the results are consistent with the idea that a variety of factors—related to both the preferences of Chinese audiences and gatekeepers—influence the likelihood of China entry. We emphasize that disentangling the influence of audiences' preferences relative to those of gatekeepers' is neither an essential question, nor the focus of our analysis. A different question—whether authorities impose a *coloristic bias* on entry outcomes—is, however, relevant to interpret our results. We address this question in Section 6.6.

5.2. Determinants of Entry into the Chinese Market

The arbitrariness and nontransparency of China's importation and content control outcomes suggest that entry into this market can never be assured. Thus, these factors support a probabilistic framework to model films' shock exposure.

We estimate probit specifications using CHINAENTRY as a dependent variable, using the comprehensive list of observable film characteristics X of Table 1 as independent variables.³⁰ Table 2 presents the obtained results. Columns 1 and 2 correspond to estimates from the sample of films released in 2009–2012; columns 3 and 4, correspond to those from the full sample. The odd-numbered columns do not account for design characteristics that are not fully controllable during production (MPAA ratings and awards). Consistent with the idea that entry into the Chinese market cannot be guaranteed, the out-of-sample predictive performance statistics (bottom of the table) suggest that, whereas negative outcomes (no entry) are predicted with high accuracy, positive outcomes are harder to anticipate. Below, we focus our discussion on the estimates of column 1, which will be used in Section 6 to derive our main results.

We first turn our attention to genre indicators. These suggest that films in genres such as action, adventure, thrillers, and romance command relatively higher China entry probabilities. These results coincide with anecdotal evidence, some suggesting that action movies with special effects have particular appeal among Chinese audiences (Rankin and Kaiman 2014) and other evidence that movie going has established itself as part of the ritual of romantic courtship in the emerging Chinese middle class (The Economist 2013).

On the other hand, comedy films exhibit systematically lower entry probabilities. This result likely stems from a large cultural discount, rooted in the fact that humor does not translate well.³¹ Interestingly, horror films also exhibit lower entry probabilities. As opposed to the previous effects, this may more directly speak to the ideological mandate of gatekeepers, as authorities are reluctant to promote superstition and, in particular, serial-killer type of violence (Martinsen 2010).³² Thus, these results illustrate that the preferences of both audiences and gatekeepers may determine China entry outcomes.

The coefficients of P75BUDGET and P90BUDGET suggest that large-budget films are more likely to enter China. This is hardly surprising as, for obvious economic arguments, large budget films must be designed to have broad appeal. The lack of statistical significance for the coefficient of BIG6STUDIO may stem from its high correlation with the budget indicators. The strongly significant and positive coefficient of 3D/IMAX coincides with reports suggesting the special adeptness of these formats to the Chinese market (Sagakian 2016).

Table 2. Probit Specifications for CHINAENTRY

	(1)	(2)	(3)	(4)
	2009–2012		2009–2015	
	Production indicators			
3D/IMAX	0.94*** (0.22)	0.88*** (0.23)	0.79*** (0.16)	0.74*** (0.16)
BIG6STUDIO	−0.08 (0.17)	−0.23 (0.16)	−0.01 (0.12)	−0.08 (0.12)
P75BUDGET	0.51*** (0.18)	0.51*** (0.18)	0.68*** (0.13)	0.63*** (0.13)
P90BUDGET	1.08*** (0.18)	1.06*** (0.19)	1.02*** (0.13)	0.96*** (0.13)
CHINESECOPROD	0.96*** (0.37)	1.00*** (0.39)	0.92*** (0.27)	0.95*** (0.28)
CHINESESTAR	1.36*** (0.44)	1.45*** (0.46)	1.10** (0.48)	1.19** (0.48)
USONLYFILM	−0.55*** (0.13)	−0.54*** (0.14)	−0.59*** (0.10)	−0.56*** (0.10)
	Genre indicators			
Action	0.56*** (0.15)	0.61*** (0.16)	0.38*** (0.11)	0.42*** (0.12)
Adventure	0.35** (0.17)	0.35** (0.18)	0.30** (0.13)	0.27** (0.13)
Animation	0.43 (0.27)	0.52* (0.29)	0.45** (0.22)	0.51** (0.23)
Comedy	−0.69*** (0.21)	−0.77*** (0.22)	−0.47*** (0.15)	−0.47*** (0.14)
Crime	−0.18 (0.19)	−0.12 (0.20)	−0.15 (0.14)	−0.09 (0.14)
Drama	−0.15 (0.15)	−0.20 (0.16)	−0.27** (0.11)	−0.30*** (0.11)
Family	0.58** (0.23)	0.75** (0.30)	0.26 (0.18)	0.37* (0.20)
Fantasy	−0.25 (0.19)	−0.29 (0.20)	−0.24* (0.14)	−0.21 (0.14)
Horror	−1.15*** (0.25)	−1.01*** (0.25)	−1.40*** (0.22)	−1.31*** (0.22)
Mystery	0.22 (0.19)	0.19 (0.20)	0.21 (0.15)	0.20 (0.15)
Romance	0.43*** (0.17)	0.41** (0.18)	0.15 (0.14)	0.11 (0.14)
SciFi	−0.02 (0.18)	−0.04 (0.20)	0.24* (0.13)	0.23* (0.13)
Thriller	0.38** (0.16)	0.44** (0.17)	0.25** (0.11)	0.26** (0.12)
Other	−0.12 (0.21)	−0.28 (0.22)	0.03 (0.14)	−0.05 (0.14)
	Sensitive content indicators			
Sex	0.03 (0.16)	0.03 (0.17)	−0.06 (0.12)	−0.10 (0.13)
Nudity	−0.34 (0.21)	−0.27 (0.22)	−0.25* (0.15)	−0.19 (0.15)
Violence	0.36** (0.15)	0.33** (0.17)	0.28*** (0.11)	0.22* (0.12)
Drug use	0.01 (0.18)	0.02 (0.19)	0.03 (0.14)	0.06 (0.13)
Strong language	−0.08 (0.15)	−0.09 (0.17)	0.06 (0.11)	0.05 (0.12)

Table 2. (Continued)

	(1)	(2)	(3)	(4)
	2009–2012		2009–2015	
	MPAA ratings			
PG		0.38 (0.33)		0.18 (0.23)
PG-13		0.58** (0.28)		0.43** (0.20)
R		0.19 (0.29)		0.16 (0.22)
	Major awards			
AWRNOM		−0.05 (0.04)		−0.00 (0.02)
AWRWON		0.35*** (0.10)		0.12* (0.07)
Constant	−1.95*** (0.22)	−2.25*** (0.26)	−1.85*** (0.17)	−2.01*** (0.19)
Observations	1,812	1,812	3,378	3,378
% Correctly predicted (all)	0.92	0.93	0.94	0.94
% Correctly predicted (positives)	0.53	0.62	0.58	0.58
% Correctly predicted (negatives)	0.97	0.97	0.98	0.98

Notes. Robust standard errors are in parentheses. The listed predictive performance metrics are computed by splitting each sample on a training (70% of observations) and a validation (30% of observations) subsamples. Models are then reestimated on the former, and predictions contrasted to outcomes in the latter (using a probability threshold of 0.5).

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

As expected, the coefficient estimate for CHINESECOPROD is positive, large, and strongly significant across specifications. However, it is interesting that this variable does not perfectly predict entry. This finding further supports the idea that entry cannot be assured.

The positive coefficient of CHINESESTAR and negative coefficient of USONLYFILM could reflect both audiences' and gatekeepers' preferences. In particular, while films with Chinese stars may be more popular among audiences, gatekeepers may also see it fit to further support their films. On the other hand, U.S.-only films may have a more marked focus on U.S. values or themes. For this reason, they may not resonate with Chinese audiences, nor with the mandate of gatekeepers.

As in most innovation contexts, the characteristics of the finalized product is not fully controllable during production. Nevertheless, these will usually still determine the product's appeal. Non fully controllable design characteristics are included in the specifications of even-numbered columns. The first of these corresponds to film ratings awarded by the MPAA. We previously described how these ratings can be important for a film's commercial success, and they cannot be perfectly anticipated during production. Even after controlling for the presence of different types of sensitive content,

results show that films with the more family oriented PG-13 rating are more likely to enter China (relative to films in the omitted R/nonrated category). The number and type of awards a film receives and is nominated for, is also a potentially important non fully controllable design characteristic.³³ Results of columns 2 and 4 support this view by suggesting that the number of major awards received can significantly increase the probability of entering China.

Although estimates across columns suggest that the determinants of film entry into China are relatively stable throughout the covered period, the value and statistical significance of some coefficients change. To investigate whether these imply a meaningful aggregate effect, we compare predicted entry probabilities across a wide set of specifications and estimation samples.

Table 3 lists the considered samples, specifications, and correlations among predicted entry probabilities. The correlations between probabilities predicted with estimates from the 2009–2012 and 2013–2015 samples (bolded) are of particular interest. Their high values suggest that the policy change did not materially alter the determinants of China entry. That is, after the new policy went into effect, the types of design characteristics that made a film more likely to enter China did not change much.³⁴ This result suggests that basing the construction of EXPOSURE on one or another set of estimates will not significantly impact our results.

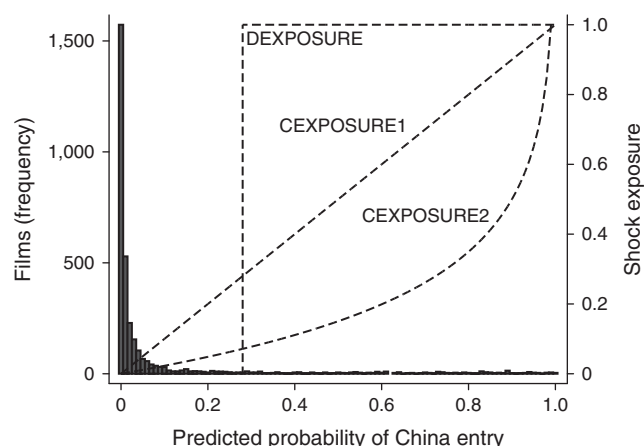
5.3. Shock Exposure

We formulate the following EXPOSURE metrics:

$$\begin{aligned} \text{DEXPOSURE}_i &= 1[\hat{\text{Pr}}(\text{CHINAENTRY} | X_i) \geq p(90)] \\ \text{CEXPOSURE1}_i &= \hat{\text{Pr}}(\text{CHINAENTRY} | X_i) \\ \text{CEXPOSURE2}_i &= \text{Normalized}(1 - \log(1 - \hat{\text{Pr}}(\text{CHINAENTRY} | X_i))). \end{aligned}$$

DEXPOSURE is an indicator variable, which is activated for films whose estimated entry probability is equal to or larger than the 90th percentile of the 2009–2012 distribution. CEXPOSURE1 corresponds to the

Figure 4. Predicted Probabilities of China Entry and Shock Exposure Metrics



Note. Predicted entry probabilities and EXPOSURE metrics are computed based on the estimates of Table 2, column 1.

predicted probability of entry, whereas CEXPOSURE2, corresponds to a convex transformation of it. The latter is included to account for the idea that the policy change may have had a larger impact at higher ranges of the predicted entry probability.³⁵ Its normalization rescales the expression inside the larger parentheses to the unit interval. We found no significant correlation between these metrics and films' production lags.

For our main analysis, we construct these metrics using the results of Table 2, column 1. Although we have shown that the determinants of China entry did not meaningfully change following the policy change, these estimates are preferred because they better reflect studios' information set as they crafted $Y^* | X$ policies in the wake of the policy change. We include extensive robustness checks showing that our main result does not hinge on this specification choice. Figure 4 presents the histogram of predicted probabilities and describes each measure graphically. This figure suggests that, for the bulk of films in the sample, the policy change may have had little impact.

Table 3. Pearson Correlations for Predicted China Entry Probabilities Under Different Specifications

Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) 2009–2010	1							
(2) 2009–2010 ¹	0.97	1						
(3) 2009–2012	0.97	0.94	1					
(4) 2009–2012 ¹	0.94	0.96	0.98	1				
(5) 2013–2015	0.91	0.88	0.95	0.93	1			
(6) 2013–2015 ¹	0.91	0.87	0.95	0.92	0.99	1		
(7) 2009–2015	0.95	0.92	0.99	0.97	0.98	0.98	1	
(8) 2009–2015 ¹	0.95	0.94	0.98	0.98	0.97	0.97	0.99	1

Note. All correlations are computed with all films in the sample and are significant at a 1% confidence level.

¹Model includes award and MPAA ratings variables.

6. Results

6.1. Light-Skin Shift

Here, we present our main result, a shift toward the more frequent inclusion of light-skinned star actors, among films with higher exposure to the policy shock. As announced in Section 1, we call this result the LSS. To do so, we operationalize Y^* through the dependent variable SHARELIGHT. We construct this variable with the aim of reflecting the likely manifestation of coloristic preferences, namely, a “light-skin premium” as opposed to “dark-skin penalty.” The results in Section 6.5 support this specification.

We define SHARELIGHT as the total number of star actors in the lightest-skin category (n_{1i}) over the total

Table 4. Average SHARELIGHT Values

	DEXPOSURE = 0	DEXPOSURE = 1
PRE ($t \leq 2013$)	0.65 (0.32)	0.65 (0.31)
POST ($t \geq 2014$)	0.66 (0.32)	0.72 (0.31)

Note. Standard deviations are in parentheses.

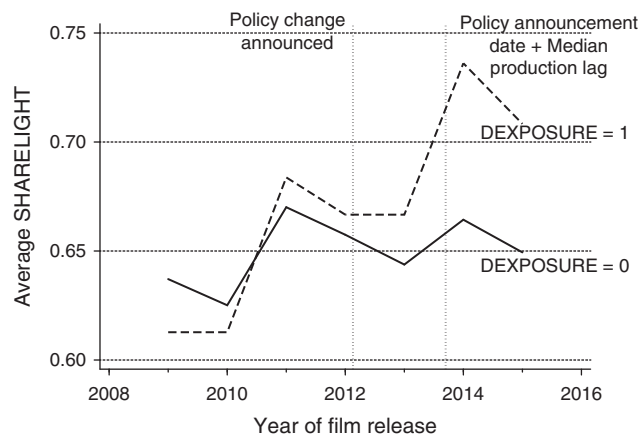
number of skin-color coded star actors in a film i (N_i). That is,

$$\text{SHARELIGHT}_i = \frac{n_{1i}}{N_i}.$$

To illustrate how SHARELIGHT traces a light-skin premium consider an alternative metric, $\text{AVGCOLOR} = (1/N_i) \sum_k k \cdot n_{ki}$. Consider also two hypothetical films i' and i'' such that $N_{i'} = N_{i''} = 2$, $n_{1i'} = n_{4i'} = 1$, and $n_{2i''} = n_{3i''} = 1$. Under AVGCOLOR, both films would rank equally under coloristic preferences, whereas under SHARELIGHT, film i' ranks higher than film i'' because it includes one actor in the lightest-skin category. Note that, since the threshold dividing skin-color categories $k = 1$ and $k = 2$ also correspond to the median of stars' skin-color distribution, SHARELIGHT also represents the share of lighter-than-median stars.

Table 4 presents descriptive evidence supporting the LSS. This table compares average values of SHARELIGHT across four groups of films. Films produced prior to the enactment of the new policy averaged SHARELIGHT values of 0.65, irrespective of shock exposure. That is, in the preperiod, two out of the three stars included in the average film belonged to the lightest skin-color category. Whereas in the postperiod this average remained virtually unchanged for films with lower shock exposure, it increased by about 0.07 for films with higher exposure to the shock.

Figure 5 unpacks these averages temporally. In the preperiod, trends are similar across exposure groups.

Figure 5. Average Shares of Light-Skinned Star Actors by Degree of Exposure to the Policy Change

In the postperiod, this trend remains roughly stable for low-exposure films but exhibits a discontinuous increase for high-exposure ones. Figure 6 presents an alternative view, by focusing on the share of films that only include light-skinned ($k = 1$) stars. The same discontinuity is observed. To further characterize the effect, we estimate the following DiD specification:

$$\text{SHARELIGHT}_i = \alpha + \beta \text{EXPOSURE}_i \times \text{POST}_{t(i)} + \Theta X_i + \lambda_{t(i)} + \epsilon_i, \quad (1)$$

where EXPOSURE corresponds to either of the measures introduced earlier. When implemented as DEXPOSURE, the specification represents a standard 2×2 design. When implemented as CEXPOSURE1 or CEXPOSURE2, EXPOSURE represents a measure of continuous “treatment intensity.”³⁶

Given the distribution of production lags, $\text{POST} = 1[t \geq 2014]$ identifies the cohorts of films that were likely produced after the policy change was announced. The term ϵ is an independent error, and λ is a release-year fixed effect. The stand-alone POST is omitted because λ makes it redundant. Variable X corresponds to the set of observables used in the China entry probit model. We do not include the stand-alone EXPOSURE variable because its variation is picked up by X . Standard checks do not unveil multicollinearity problems. Throughout our analysis, we report and draw inferences from robust standard errors.

The parameter of interest is β . An estimate $\hat{\beta} \neq 0$ would suggest that, after the new policy went into effect, films with more “China-oriented” characteristics X , altered star casting guidelines. An estimate $\hat{\beta} > 0$ would be consistent with the descriptive evidence by implying that such alteration favored light-skinned actors. Studios’ ability to choose X introduces a natural concern about this inference. We address this concern in Section 6.3, finding no evidence to support it.

This DiD specification is useful because it controls for two important forms of confounds. We previously illustrated one of these by citing films inspired by World

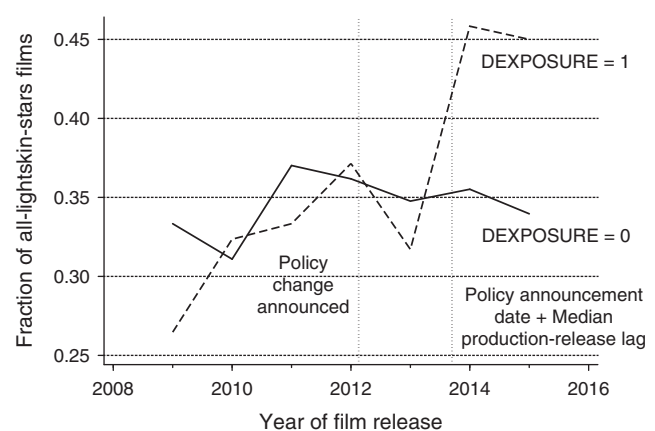
Figure 6. Average Fraction of All-Light-Skinned-Stars Films

Table 5. Differences-in-Differences Specifications for SHARELIGHT

	(1) DEXPOSURE	(2) CEXPOSURE1	(3) CEXPOSURE2
EXPOSURE	0.08**	0.13**	0.22**
× POST	(0.03)	(0.05)	(0.10)
	[0.02]	[0.01]	[0.02]
Observations	3,268	3,268	3,268

Notes. EXPOSURE metrics are computed with the estimates of Table 2, column 1. Estimated models include release-year fixed effects as well as the controls X used in the China entry specification referenced above. Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Wars I and II, which develop stories that are better suited for light-skinned characters. If this was pervasive in the sample, we may observe baseline differences in the propensity to cast light-skinned stars among films with different characteristics. This effect is controlled for by including the set of control variables X as explanatory variables. In addition, there may exist unobserved temporal variation, possibly arising from shifting conditions in the actors' job market, or from changes in disposable income across consumer segments.³⁷ This form of unobserved variation is accounted for by the release-year fixed effects. The results below suggest that these temporal trends do not differ based on shock exposure.

Table 5 presents the estimated β coefficients. These point to a robust, positive impact of the policy change on average SHARELIGHT values. The direct correlate of Figure 5—the estimate obtained when using DEXPOSURE (column 1)—is similar to that implied by the graph. It suggests that, as a result of the new policy, the share of actors in the lightest skin category increased by about 8% among films in the top exposure decile. Results from continuous EXPOSURE metrics suggest that this effect may have been as large as 22%, for the films with highest measure exposure.

As we noted in Section 3.2, the announcement of the new policy was preceded by a series of legal disputes and sustained pressure by the United States to get China to relax (or eliminate) restrictions on foreign film importation. This leads us to question whether, observing this sequence of events, Hollywood studios may have anticipated the 2012 relaxation and accordingly adapted film design in years prior. To address this question we estimate

$$\text{SHARELIGHT}_i = \alpha + \sum_{t' \geq 2010} \beta_{t'} \text{EXPOSURE}_i \times \mathbf{1}[t(i) = t'] + \Theta X_i + \lambda_{t(i)} + \epsilon_i.$$

Here, the parameter vector $\{\beta_{2010}, \dots, \beta_{2015}\}$ picks up the pattern by which the LSS unfolded across successive film cohorts. (β_{2009} is normalized to zero to avoid

Table 6. Temporal Unfolding of the Light-Skin Shift

	(1) DEXPOSURE	(2) CEXPOSURE1	(3) CEXPOSURE2
EXPOSURE	0.02	0.12	0.19
× $\mathbf{1}[t = 2010]$	(0.06)	(0.09)	(0.22)
	[0.66]	[0.18]	[0.40]
EXPOSURE	0.03	0.12	0.26
× $\mathbf{1}[t = 2011]$	(0.05)	(0.09)	(0.23)
	[0.55]	[0.21]	[0.25]
EXPOSURE	0.03	0.13	0.30
× $\mathbf{1}[t = 2012]$	(0.06)	(0.10)	(0.24)
	[0.59]	[0.19]	[0.21]
EXPOSURE	0.02	0.06	0.00
× $\mathbf{1}[t = 2013]$	(0.05)	(0.09)	(0.28)
	[0.68]	[0.54]	[0.99]
EXPOSURE	0.09*	0.19**	0.29*
× $\mathbf{1}[t = 2014]$	(0.05)	(0.08)	(0.17)
	[0.10]	[0.02]	[0.08]
EXPOSURE	0.10*	0.23***	0.47***
× $\mathbf{1}[t = 2015]$	(0.05)	(0.08)	(0.17)
	[0.06]	[0.00]	[0.01]
Observations	3,268	3,268	3,268

Notes. EXPOSURE metrics are computed with the estimates of Table 2, column 1. Estimated models include release-year fixed effects as well as the controls X used in the China entry specification referenced above. Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

collinearity.) Anticipatory effects would be reflected by $\hat{\beta}_t > 0$, for some $t < 2014$.

Estimates are shown in Table 6. Because statistical significance arises only among the 2014 and 2015 cohorts, these suggest that there were no anticipatory effects. Note that the LSS seems to have unfolded gradually in 2014–2015. In particular, we obtain $0 < \hat{\beta}_{2014} < \hat{\beta}_{2015}$, across EXPOSURE metrics. This pattern could be rationalized, for example, if at the time the new policy was announced, a greater share of castings had been defined for the 2014 than the 2015 cohort of films. In turn, this result insinuates that the magnitude of the LSS may have continued to grow during the following years. Last, note that these results also imply that “pre-trends” did not differ based on shock exposure.³⁸

6.2. Robustness and Falsification

6.2.1. Robustness. Here we address a series of caveats about the above results. To save space, unless noted, supporting tables and figures are presented in the online appendix.

We start by noting that one could be concerned that the skin-color coding procedure introduces a violation of ϵ 's independence assumption. This would be a particularly serious problem if coding errors favored light-skin coding among actors that appear in post films with high exposure to the shock. This pattern would entail an upward bias on $\hat{\beta}$, and potentially lead us to conclude that there was an LSS when in fact there was none.

This violation is a priori unlikely because many actors star in both pre and post films, with different degrees of shock exposure. We nevertheless assembled the distributions of within-actor coding discrepancies, across exposure levels and periods. The cited violation would be reflected by a $\text{DEXPOSURE} = \text{POST} = 1$ distribution with relatively higher skewness. However, all distributions have roughly the same symmetric shape.

Next, we reproduced our main results of Table 5, but instead categorizing actors' skin color according to the median score awarded by MTurk coders. Estimates are similar and statistical significance is preserved. We then considered alternative exposure metrics, computed from the different subsamples and specifications for the China entry probit. Results remain largely robust. We proceeded to implement a bootstrapping procedure to account for the stochasticity of the exposure metrics.³⁹ The resulting distributions yield all strictly positive β estimates ($p = 0$), with medians that closely trace the estimates of Table 5.

Last, we replicated the analysis using a matched-samples approach instead. Based on the vector of observed characteristics X , we partitioned the sample of films into groups $g = 1, \dots, G$ using k -means clustering. With these, we computed $\Delta_g = \mathbb{E}[\text{SHARELIGHT} \mid g, \text{POST} = 1] - \mathbb{E}[\text{SHARELIGHT} \mid g, \text{POST} = 0]$. The analysis presented in the online appendix suggested the use of $G = 190$, which left us with 176 matched observations. We then regressed this difference on a constant and the exposure variable, which is now defined at the cluster level, computed based on cluster-specific averages of X , and has the same interpretation as before. Results are presented in Table 7. The small value of the constant suggests that observations were overall closely matched, and that the pre/post differences in average SHARELIGHT values are solely mediated by films' degree of exposure to the shock. These results reaffirm those obtained from our baseline DiD approach.

6.2.2. Falsification. To further investigate the validity of the causal interpretation of β , we carried out three

falsification tests. In the first of these we dropped films released in 2013–2015 and imposed 2011 as a falsified date for the policy change. That is, we are falsely assuming that the 2011 and 2012 film cohorts were produced after the policy change was announced. The resulting coefficient estimates are presented in panel A of Table 8. They show that our DiD regression correctly delivers a statistically insignificant $\hat{\beta}$.

Our second test focused on the 110 animation films in the sample. In most cases, an actor's physical characteristics do not map into the characteristics of the animated character that they play—the actor's contribution to the films is almost entirely circumscribed to their voice. Furthermore, as can be seen from a quick Google Images search for the query “Animation Film Posters,” images of starring actors tend to not appear in promotional material. Therefore, the heightened relevance of Chinese coloristic preferences should have been less important for the casting of these actors. Panel B of the table presents the results. Resulting $\hat{\beta}$ values imply a consistently null effect.

Last, we implement a test that exploits the same rough logic, but that focuses on the casting outcomes among the 324 voice roles observed in the sample. As with animation films, coloristic preferences should be less important in this case. Using a probit model, we tested whether the probability that these roles are played by a light-skinned actor ($k = 1$) increased as a result of the new policy. Estimates are presented in panel C of the table. These show consistently null effects.

Table 8. Falsification Tests

	(1) DEXPOSURE	(2) CEXPOSURE1	(3) CEXPOSURE2
A. 2009–2012 subsample, $\text{POST} = 1[t \geq 2011]$			
EXPOSURE \times POST	−0.04 (0.04) [0.33]	0.01 (0.07) [0.86]	0.21 (0.18) [0.24]
Observations	1,745	1,745	1,745
B. Animation films			
EXPOSURE \times POST	0.08 (0.12) [0.51]	−0.10 (0.21) [0.62]	−0.33 (0.63) [0.61]
Observations	110	110	110
C. Voice role played by pale-skinned ($k = 1$) actor (Probit)			
EXPOSURE \times POST	0.21 (0.35) [0.55]	−0.39 (0.55) [0.48]	−1.22 (1.43) [0.39]
Observations	324	324	324

Notes. Panels A and B: OLS specifications. Panel C: probit specification. EXPOSURE metrics are computed with the estimates of Table 2, column 1. Estimated models include release-year fixed effects as controls X . Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7. Estimates from the Matched-Samples Procedure

	(1) DEXPOSURE	(2) CEXPOSURE1	(3) CEXPOSURE2
EXPOSURE	0.11** (0.06) [0.05]	0.15** (0.07) [0.02]	0.19** (0.08) [0.02]
Constant	0.01 (0.02) [0.59]	0.00 (0.02) [0.97]	0.00 (0.02) [0.81]
Observations	176	176	176

Notes. OLS results. The matching procedure is described in the text. Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

6.3. Endogenous Design Characteristics

6.3.1. Observable Characteristics. As pointed out earlier, our main inference may be confounded by studios' ability to choose films' design characteristics. In particular, after the new policy was announced, some studios may have decided to *redirect* their innovation toward sets of characteristics that are more amenable to Chinese audiences.

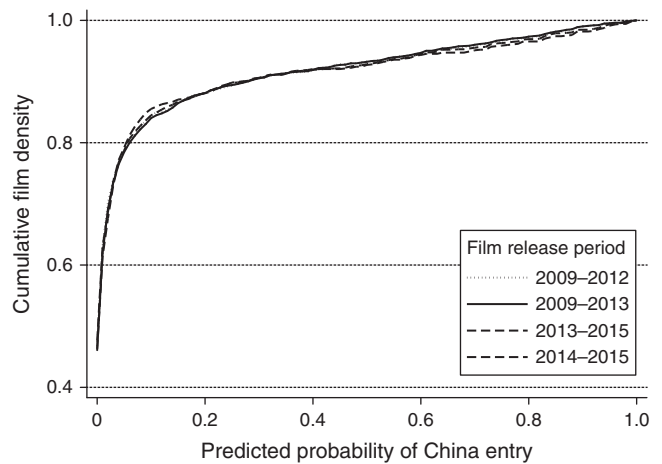
To see the problem, consider an example. Our results of Section 5.2 showed that Action and large-budget films are more likely to enter China. Also recall our running example of films inspired on World Wars, which are usually associated to the action genre, and better suited for light-skinned characters. If, in response to the new policy, studios began to allocate large budgets to World War films more often, these will be associated with generally higher EXPOSURE values in the post period. In this scenario, the documented LSS may not be entirely rooted on an alteration of casting guidelines, but also on the “artificial inflation” of EXPOSURE among this type of films, which is better suited for light-skinned characters.

Before addressing this issue empirically, we must note that, although studios “choose X ,” they do so under constraints. In particular, large studios (which produce most of the highly exposed films in the sample) employ “portfolio strategies” aimed at curtailing their aggregate risk exposure (Vogel 2014). These strategies limit the extent to which design characteristics X can be reshuffled across films within a studio's portfolio, as diversification will usually require them to cover different genres (Perretti and Negro 2007) and budget levels (Pokorny and Sedgwick 2010). Furthermore, because films targeting Chinese audiences are riskier (China entry cannot be assured), they may reinforce the need to maintain well-diversified portfolios.

To evaluate this “redirection hypothesis,” we present Figure 7, which displays the cumulative distributions of new films along the support of predicted China entry probabilities. The dotted and solid lines correspond to distributions obtained on the subsample of films produced before the new policy was announced (pre films); dashed lines, to those obtained from the subsample of films produced after it (post films).⁴⁰

The redirection hypothesis would be reflected here by a distribution of post films that places relatively more mass on higher spectra of predicted entry probabilities. That is, we should observe that postdistribution first-order stochastically dominates the predistribution. However, we observe almost no difference. The Kolmogorov–Smirnov test for the equality of continuous distributions confirms this graphical finding. In the online appendix we include regression-based analysis, which provides evidence to the same point. Thus, this result suggests that the new policy did not cause a “Chinese-oriented redirection” of overall innovation

Figure 7. Film Distribution Along the Support of China Entry Probabilities



Note. Predicted probabilities of China entry are computed from estimates of Table 2, column 1.

patterns, which in turn alleviates the concerns stemming from the potential endogeneity of X .

6.3.2. Unobservable Characteristics. Our results so far indicate that, although the new policy prompted studios to use different casting criteria, it did not prompt them to choose more China-oriented vectors of observable characteristics X . Nevertheless, studios may have adjusted other design characteristics that are not observed in the data. Although this hypothesis cannot be completely ruled out, it is possible to address a milder version of it. Namely, one focusing on a leading form of unobservable design characteristic: storylines. Here we test this hypothesis. We find no support for it.

It is important to first highlight that such an impact on storylines would not be inconsistent with cultural accommodation. This impact would nevertheless blur the interpretation of the LSS—it would suggest that, at least in part, the LSS may have been the subproduct of a shift to storylines that are better suited for light-skinned characters. Since we do not observe this impact on storylines, we revert to interpreting the LSS as a directly controlled outcome. In particular, as an alteration of casting guidelines “holding storylines constant.”

Our empirical test relies on a measure of storyline similarity between pairs of films. To generate a similarity metric, we draw from Eliashberg et al. (2007 and 2014), who apply natural-language processing to films' text descriptions. In particular, these authors use a “bag-of-words” (BW) approach to systematically address the nature of films' storylines and covered themes, information that then proves helpful to predict commercial performance.

As emphasized by the first of these articles (and implemented by the second), natural-language processing techniques would be ideally applied to scripts, which

provide rich descriptions of films' storylines. However, scripts are not publicly available on a systematic basis.⁴¹ Thus, like in Eliashberg et al. (2007), we apply BW to shorter texts that summarize storylines. In particular, we use IMDb's "summary plot" and "synopsis" entries, which are available on a reasonably systematic basis. Plots are shorter and less structured than synopsis.⁴² Many films have more than one summary plot posted on the website whereas, when available, there is only one synopsis. After discarding nonusable entries, plots are available for about 80% of nonanimation films in the sample. Synopsis are available for about 44%.

BW codifies each text description as a vector of word densities. Film similarity can then be assessed by comparing their distributions. To make these comparisons we employ the "cosine similarity" metric, which is commonly used for this purpose because of its intuitive formulation (Singhal 2001). Namely, this metric approaches zero for highly dissimilar vectors, and one for highly similar ones. Intermediate values codify intermediate degrees of similarity. To avoid common confounds, we run the algorithm on a preprocessed data set.⁴³ For every pair of text descriptions (i, j) , we label the resulting variable SIMILARITY_{ij} .

The resulting distribution of SIMILARITY provides some validation for the approach. For example, even though used texts do not include films' titles, there is a strong convergence of themes among pairs with the highest SIMILARITY values.⁴⁴ Furthermore, the average plot- SIMILARITY among same-film pairs is over five standard deviations larger than that for different-film pairs. A final piece of validating evidence is available from the idea that higher SIMILARITY values should be expected from pairs of films associated to the same sets of genres, or that exhibit similar types of sensitive content.⁴⁵ That is, SIMILARITY should decrease with the "distance" between two films' genre and sensitive content profiles. To verify this, we measured this distance through the Euclidean norm of vectors of genre and sensitive content indicators (respectively, $\|X_{ij}^G\|$ and $\|X_{ij}^C\|$), and estimated

$$\text{SIMILARITY}_{ij} = \gamma + \phi \|X_{ij}^G\| + \varphi \|X_{ij}^C\| + \epsilon.$$

Our hypothesis is supported by negative, statistically significant estimates for ϕ and φ . These results are presented in the online appendix.

Using SIMILARITY , we now test whether higher shock exposure can be linked to larger changes in films' storylines. We rely on the clustering procedure used before, which partitioned the sample of films into groups $g = 1, \dots, 190$ based on their observable design characteristics X . We construct a sample composed of unique, nonordered film pairs (i, j) that belong to the same group g . We further restrict the sample to the set of pairs that either include two films produced before

the policy change, or that include one produced before and the other after it. That is, we consider the sample in which each observation is a pair of films in the set $\{(i, j): i \neq j, g(i) = g(j), \text{POST}(t(i)) \times \text{POST}(t(j)) = 0\}$. Defining $\text{CROSSPER}_{ij} = 1[\max\{\text{POST}(t(i)), \text{POST}(t(j))\} = 1]$ to identify pairs that include one film produced after the policy change, we estimate

$$\begin{aligned} \text{SIMILARITY}_{ij} \\ = \alpha + \beta \text{EXPOSURE}_g \times \text{CROSSPER}_{ij} + \mu_g + \epsilon, \end{aligned}$$

where μ_g represents a cluster-specific fixed effect. A stand-alone EXPOSURE variable is omitted because μ_g makes it redundant. As in our earlier analysis, EXPOSURE is computed based on cluster-specific averages. Recall that, since all pairs in the constructed sample have been matched on X , including these as independent variables does not add much information.⁴⁶ With this, β picks the potential impacts of the policy change on storylines. In particular, this parameter captures the potential role of EXPOSURE as a mediator of cross-period differences in SIMILARITY . An estimate $\hat{\beta} < 0$ would indicate that storylines were altered as a consequence of the policy change.

Panel A of Table 9 presents the results obtained from the plots data. These suggest that storylines were not impacted. Results obtained from the synopsis data (panel B) yield the same conclusion. This finding is supported by further results presented in the online appendix, which rely on a more sophisticated natural-language processing technique,

Table 9. Storyline Similarity

	(1) DEXPOSURE	(2) CEXPOSURE1	(3) CEXPOSURE2
A. Summary plots			
EXPOSURE × CROSSPER	−0.001 (0.00) [0.61]	−0.003 (0.00) [0.36]	−0.003 (0.00) [0.42]
Constant	0.051*** (0.00) [0.00]	0.051*** (0.00) [0.00]	0.051*** (0.00) [0.00]
Observations	23,177	23,177	23,177
B. Synopsis			
EXPOSURE × CROSSPER	0.004 (0.01) [0.56]	0.013 (0.01) [0.13]	0.013 (0.01) [0.26]
Constant	0.086*** (0.00) [0.00]	0.085*** (0.00) [0.00]	0.086*** (0.00) [0.00]
Observations	5,201	5,201	5,201

Notes. EXPOSURE metrics are computed with the estimates of Table 2, column 1. Estimated models include cluster-specific fixed effects. Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Term Frequency-Inverse Document Frequency (TF-IDF), which gives more weight to words that are more frequent in a particular document, and less weight to those that are more frequent in the entire collection of texts in the sample (Leskovec et al. 2014). Thus, we conclude that the policy change did not alter the nature of storylines developed by films targeting the Chinese market. In turn, this conclusion supports interpreting of the LSS as the result of a direct control of casting guidelines.

6.4. A Superstar Shift?

The distribution of actors' skin colors in the sample (Figure 2) shows that the majority of star actors have a generally light skin tone. Based on this observation, one may wonder whether the LSS was motivated by the more frequent casting of more popular/famous actors (superstars), but who happen to be light skinned. If this "superstar shift" hypothesis was true, we should conclude that the LSS was not motivated by the strive to cast more pale-skinned stars, but instead, more popular ones.

Before turning to our analysis, we note that, although entirely plausible, the superstar shift could be tempered by supply side and demand-side factors. Namely, by definition, there is a limited number of superstars who can appear in a limited number of films. From a demand perspective, superstars may also be "too expensive" to be used as a "wink" to Chinese audiences, particularly given that entry into that market cannot be assured.

To address this question we retrieved IMDb's "Starmeter" data, which has been previously used as a proxy for actors' fame/popularity (Mathys et al. 2016, Karniouchina 2011). IMDb (2018) describes this metric as a measure of "what people are interested in, based not on small statistical samplings, but on the actual behavior of millions of IMDb users." The website constructs it using proprietary, undisclosed methods, based on the in-site search behavior of the over 250 million monthly IMDb users. The resulting metric enables a ranking, with lower values indicating higher popularity.

We obtained complete Starmeter series for each actor in the sample. Values are reported at the weekly level. Reflecting promotional activities and viewership, these series exhibit considerable short-time variation, which we mute by averaging within years. For each actor/film combination, we consider this value during the year prior to the film's release. For an actor a featuring in film i , we label this variable as $FAME_{ai}$. Given the definition of the Starmeter metric, lower values of FAME indicate higher popularity.⁴⁷

To investigate the validity of FAME, we first look at the number of roles played by each actor. Here, we would expect more famous actors to play a larger number of roles. Data confirm this prediction.⁴⁸ Next, we

consider films' budget levels. In this case, we would expect higher-budget films to cast more famous actors. The data also confirm this prediction, by showing that films with top 25% and top 10% budgets are much more likely to cast the 10% and 1% more popular stars. The supporting table is presented in the online appendix.

Our test relies on the variable SHARELIGHT_FAME90 _{i} , which is computed as the share of star actors in a film i , who both (i) belong to the lightest-skin category ($k = 1$), and (ii) belong to the 90% less popular actors within the set of all those starring in films released in a given year. That is, SHARELIGHT_FAME90 reflects the participation of light-skinned, nonsuperstar actors in each film. We then regress SHARELIGHT_FAME90 on specification (1). An estimate $\hat{\beta} > 0$ would lead us to conclude that the LSS was not driven by a shift toward light-skinned superstars, and thus reject the superstar shift hypothesis.

Panel A of Table 10 shows the estimated coefficients. These point to $\hat{\beta} > 0$, prompting the rejection of the superstar shift hypothesis. In fact, these estimates are somewhat larger than those obtained from the baseline SHARELIGHT variable, suggesting that the LSS may have represented a stronger turn toward not-so-popular light-skinned actors. Panel B shows analog results for SHARELIGHT_FAME99, which is constructed analogously, but focusing on the 99% less popular actors. These results also suggest that the hypothesis should be rejected.

Table 10. The Superstar Shift Hypothesis

	(1) DEXPOSURE	(2) CEXP0SURE1	(3) CEXP0SURE2
A. SHARELIGHT_FAME90			
EXPOSURE \times POST	0.10** (0.04) [0.02]	0.18*** (0.06) [0.00]	0.35*** (0.13) [0.01]
B. SHARELIGHT_FAME99			
EXPOSURE \times POST	0.08* (0.04) [0.05]	0.14** (0.06) [0.01]	0.29** (0.13) [0.03]
C. SHARELIGHT_CHINAFAME90			
EXPOSURE \times POST	0.06 (0.04) [0.14]	0.10* (0.06) [0.07]	0.23* (0.13) [0.07]
D. SHARELIGHT_CHINAFAME99			
EXPOSURE \times POST	0.06 (0.04) [0.13]	0.11** (0.06) [0.05]	0.21* (0.13) [0.09]
Observations	3,268	3,268	3,268

Notes. OLS estimates for specification (1). Dependent variables are defined in the text and listed as each panel's title. EXPOSURE metrics are computed with the estimates of Table 2, column 1. Estimated models include release-year fixed effects as controls X . Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Although Chinese people have for some time now been able access to IMDb, it is possible that Starmeter data do not accurately reflect popularity in China. To evaluate whether this caveat changes our results, we would ideally employ a variable like the IMDb's Starmeter, but which is constructed based on the browsing behavior of Chinese people only. Having been unable to identify such data, we leverage the available information from IMDb.

Following the results of Mathys et al. (2016)—which suggest that an actor's previous number of roles increases consumer interest in the actor's personal brand—we adjust FAME by each actor's number of starring roles in China releases prior to the release of film i ($PREVCHINAROLES_{ai}$).⁴⁹ We construct $CHINAFAME_{ai}$ as

$$CHINAFAME_{ai} = \frac{FAME_{ai}}{1 + PREVCHINAROLES_{ai}}.$$

Note that, because lower values of FAME represent higher popularity, a larger value of $PREVCHINAROLES$ increases the popularity in China that is measured by $CHINAFAME$.⁵⁰ Using this variable, we construct and analyze $SHARELIGHT_CHINAFAME90$ and $SHARELIGHT_CHINAFAME99$ as before. Panels C and D of Table 10 present the results. Although the estimates are somewhat smaller and estimated less precisely, they still evidence the LSS. We conclude that, although Chinese popularity seems to have a sustained part of the LSS, it did not drive the effect.

6.5. Composition

Our review of coloristic preferences in China suggested that these may manifest more like a light-skin premium than a dark-skin penalty, and that the pale-skin standard may be more stringent for female than male beauty. In this section we investigate whether the composition of the LSS supports these insights.

To implement this analysis we construct a data set with observations defined at the role ($r = 1, \dots, R$) level. That is, observations correspond to unique film/actor combinations. We then divide this data set in two subsamples, one corresponding to all of the roles played by females; the other to those played by males. As in our main analysis, we drop voice roles and animation films. In the resulting sample, there are 2,779 male actors, who play 5,683 roles. There are 1,863 actresses, who play 3,541 roles. In the online appendix we show that the policy change did not alter the proportion of roles played by each.

For the lightest ($k = 1$) and darkest ($k = 4$) skin-color categories, we define the indicator $y_r^k = \mathbf{1}[\text{The individual who plays role } r \text{ belongs to skin color category } k]$ and estimate the following equation separately on each subsample:

$$y_r^k = f(\alpha + \beta \text{EXPOSURE}_{i(r)} \times \text{POST}_{t(i(r))} + \Theta X_{i(r)} + \lambda_{t(i(r))}),$$

Table 11. Composition of the Light-Skin Shift

	(1) DEXPOSURE	(2) CEXPOSURE1	(3) CEXPOSURE2
A. Female role played by light-skinned ($k = 1$) actress			
EXPOSURE \times POST	0.41* (0.21) [0.06]	0.73** (0.31) [0.02]	1.14* (0.68) [0.09]
Observations	3,541	3,541	3,541
B. Female role played by dark-skinned ($k = 4$) actress			
EXPOSURE \times POST	−0.20 (0.41) [0.63]	−0.07 (0.78) [0.93]	1.49 (1.39) [0.28]
Observations	3,156	3,156	3,156
C. Male role played by light-skinned ($k = 1$) actor			
EXPOSURE \times POST	0.16 (0.12) [0.17]	0.25 (0.18) [0.16]	0.59 (0.42) [0.16]
Observations	5,683	5,683	5,683
D. Male role played by dark-skinned ($k = 4$) actor			
EXPOSURE \times POST	−0.10 (0.20) [0.62]	−0.24 (0.32) [0.45]	−0.90 (0.90) [0.32]
Observations	5,654	5,654	5,654

Notes. Probit specifications. The dependent variables are defined as $\mathbf{1}[\text{Female (male) role played by female (male) actor in skin color category } k]$. EXPOSURE metrics are computed with the estimates of Table 2, column 1. Estimated models include release-year fixed effects as controls X . Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

where f corresponds to the probit functional form. When estimated using y_r^1 on the subsample of female roles, an estimate $\hat{\beta} > 0$ would suggest that the policy change increased the probability that female roles are played by light-skinned actresses. Analogously, if we were to obtain $\hat{\beta} < 0$ on the same subsample, but instead use y_r^4 as the dependent variable, we should conclude that the policy change led to a decrease in the probability of female roles being played by actresses that belong to the darkest skin-color category. While both these results would be consistent with the LSS, only the former would support the light-skin premium view.

Results are shown in Table 11. Panels A (for y_r^1) and B (for y_r^4) refer to the subsample of female roles; panels C and D, refer to male roles.⁵¹ Consistent with the more important role of pale skin for female beauty standards, patterns of statistical significance suggest that the LSS primarily unfolded through female roles. Furthermore, this effect is shown to have manifested through the more frequent casting of pale-skinned actresses rather than the less frequent casting of those with dark-most skin colors. The estimate of column 1 in panel A implies that, evaluated at the mean, the probability that a female role of a DEXPOSURE = 1 film is played by one of the former, increased by about 12% as a consequence of the policy change.

6.6. Were Gatekeepers Responsible for the Light-Skin Shift?

We have previously emphasized that China entry outcomes depend on the composition of preferences of Chinese audiences and gatekeeping authorities. Even though the stated ideological mandate faced by the latter does not offer grounds to suspect that they may impose a coloristic bias on entry or censorship outcomes, one may still wonder if, at least in part, their preferences may drive the documented LSS. Here we test this hypothesis. Results suggest that gatekeepers do not impose a coloristic bias, which leads us to conclude that the LSS was fundamentally driven by the preferences of Chinese audiences.

Our test compares patterns of film entry into (Mainland) China against those into two “control” markets, Taiwan and Hong Kong. Because of their deep cultural connections, these three markets are likely to have similar preferences, particularly coloristic ones. Moreover, because Taiwan and Hong Kong do not restrict film imports, a comparison thereof can shed some light regarding the potential biases imposed by the gatekeepers of the Mainland Chinese market.

Despite the existence of many nontrivial differences across these markets, the existence of a relatively large degree of cultural similarity can be argued on the grounds of a shared history. First and foremost, recall that the degree of political independence that Hong Kong and Taiwan have today has been achieved in relatively recent historic times, over two millennia after coloristic preferences were forged (Dikötter 1992). Today, populations remain ethnically similar and overwhelmingly homogeneous across the three markets: over 90% of the population of each is ethnic Han.⁵² Furthermore, skin-whitening cosmetics are about equally important for all of them (World Health Organization 2011, Tan 2012). Importantly, however, in contrast to the Mainland China case, film imports into Taiwan and Hong Kong are largely unregulated. Thus, entry outcomes into these markets are fundamentally driven by the preferences of their audiences.⁵³

In our data, the openness of the Hong Kong and Taiwanese markets is reflected by the total entry statistics, which appear at the bottom of the Table 12.⁵⁴ Despite the fact that the Mainland China market is about 25 times larger than each of the other two, the number of films that enter them is at least double that of films that enter Mainland China. Statistics in this table also insinuate a high degree of preference overlap. For example, out of all of the films that entered either Hong Kong or Taiwan, over 55% entered both markets. In addition, only 30 out of 248 films that entered Mainland China did not enter Hong Kong or Taiwan. As a comparison, when we consider two different Asian markets, Vietnam and Thailand, this number is more than double.

Table 12. Descriptive Statistics for Entry into Mainland China, Hong Kong, and Taiwan (2009–2015)

Markets	Number of films	Percent (%)
Mainland China only	30	3.3
Hong Kong only	200	21.8
Taiwan only	135	14.7
Mainland China and Hong Kong only	35	3.8
Mainland China and Taiwan only	16	1.8
Hong Kong and Taiwan only	333	36.4
Mainland China, Hong Kong, and Taiwan	167	18.2
Total Mainland China, Hong Kong, or Taiwan	916	100
Total Mainland China	248	
Total Hong Kong	735	
Total Taiwan	651	

To investigate the hypothesis of interest we first consider the entry probit model of Section 5.2. We enrich its specification by adding SHARELIGHT and an indicator activated for films that enter either Taiwan or Hong Kong (TWHKENTRY).⁵⁵ By including the latter, the specification controls for the common appeal of the films’ overall design across markets. Because stars’ skin color is part of this overall design, and Hong Kong and Taiwan do not have gatekeepers, the coefficient of SHARELIGHT captures the potential coloristic bias of Chinese gatekeepers. Table 13 presents the results, for three variants of the used specification. Because the coefficients for SHARELIGHT and its interaction with POST are statistically insignificant, neither set of results supports the alleged bias of Chinese authorities.

Table 13. Probability of Entry into Mainland China as a Function of SHARELIGHT and Entry into Taiwan or Hong Kong

	(1)	(2)	(3)
HKTWENTRY	0.71*** (0.15) [0.00]	0.69*** (0.15) [0.00]	0.69*** (0.15) [0.00]
SHARELIGHT	−0.10 (0.16) [0.54]	−0.11 (0.16) [0.50]	−0.23 (0.20) [0.26]
SHARELIGHT × POST			0.26 (0.31) [0.40]
Release year fixed effects	No	Yes	Yes
Observations	3,268	3,268	3,268

Notes. Probit estimates. Models are estimated on the full sample of film and include the controls X used in the China entry specifications of odd-number columns in Table 2. POST is implemented as $1 = [t \geq 2013]$. Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

A potential weakness of this test is that it implicitly assumes that all Mainland China entry outcomes in the sample contain useful information. If not all films attempted to enter Mainland China, the influence of the hypothesized bias could be muted by the variation along other design dimensions.⁵⁶ To address this issue, we restrict the attention to the 916 films released in at least one of the three markets. Note that, when comparing a film i 's entry outcome into Mainland China and into a market m (Hong Kong, Taiwan), there are three possible outcomes, described by the definition of the variable z

$$z_{im} = \begin{cases} 3 & \text{if } i \text{ enters Mainland China but not } m, \\ 2 & \text{if } i \text{ enters } m \text{ and Mainland China,} \\ 1 & \text{if } i \text{ enters } m \text{ but not Mainland China.} \end{cases}$$

Under the hypothesized bias, higher SHARELIGHT values would foster the transition from the first to the second outcome and, in extreme cases, to the third.

Our second test rationalizes the variation of z with the following specification:

$$z_{im} = f(\alpha + \beta \text{SHARELIGHT}_i + \Theta X_i + \lambda_{t(i)}),$$

where f corresponds to ordered probit functional form, X represents the set observable design characteristics, and λ are release-year fixed effects. Parameter β captures the role of SHARELIGHT as a mediator of differential entry outcomes. The hypothesized bias would be supported by a positive estimate of this parameter.⁵⁷ Table 14 presents the obtained results. The lack of statistical significance means that the results support neither a baseline coloristic bias of Chinese gatekeepers, nor an accentuation thereof following the enactment of the new policy.

We conclude by noting that the relevance of coloristic preferences among Chinese audiences could be investigated in a more direct way using revenue data, and

Table 14. Differential Probabilities of Entry into Mainland China, Hong Kong, and Taiwan

	(1)	(2)	(3)	(4)
	Mainland China and Hong Kong		Mainland China and Taiwan	
SHARELIGHT	−0.24 (0.19) [0.20]	−0.29 (0.22) [0.19]	−0.28 (0.19) [0.14]	−0.30 (0.26) [0.24]
SHARELIGHT × POST		0.11 (0.36) [0.77]		0.04 (0.34) [0.91]
Observations	781	781	716	716

Notes. Ordered probit specifications. Estimated models include release-year fixed effects as well as the controls X used in the China entry specifications of odd-number columns in Table 2. POST is implemented as $1 = [t \geq 2013]$. Robust standard errors are in parentheses and p -values are in brackets.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

guided by the question, “do films with higher SHARELIGHT values produce superior competitive outcomes in Mainland China relative to in the United States?” Such a strategy would face the usual hurdles of demand estimation, which in this case would include endogenous allocation of promotional resources and release configurations (e.g., number and types of screens in which the film is shown, and the amount of time it is shown for). It would also face the doubts cast by allegations of manipulations of box-office figures in China (Lang 2017). We are assembling a data set to pursue this approach in future research.

7. Conclusion

Discussing the China release of “Transformers: Age of Extinction” (2014), Sony Pictures executive Nigel Clark wrote the following:

The seamless integration of the Chinese elements mentioned above, without the appearance of tokenism, is perhaps the most important key to the appeal of the film to the mainstream Chinese audience.⁵⁸

In this paper we have shown that, beyond anecdote, many large Hollywood productions have accommodated their design to elements of the Chinese culture. Whereas in the above statement, Clark primarily refers to the kind of childhood memories that are deeply held by many Chinese adults, we illustrate the point through another distinctive, although more generalized and socially sensitive element of their culture: a marked aesthetic preference for light skin.

The influence of Chinese culture is taken here as an example of a wider-ranging phenomenon: the economic rise and integration of emerging markets has created an influx of “newly endowed” consumers into the global demand for products and services. Because these consumers are known to differ considerably from their counterparts in developed markets in many cultural and behavioral respects, their “global activation” may also imply a shift of aggregate preferences in the total addressable market for international products and services, and thus condition their optimal design.

Although marketing scholars have widely acknowledged and explored the nature and implications of these differences, these have not yet been shown to have the type of first-order, unexpected global impact that we demonstrate. Like Chandy and Narasimhan (2015, p. 261)—who state that “the changes that are happening in emerging markets today are unprecedented—in scale, scope, and speed—in human history”—we interpret this finding as a testament to their newly acquired global influence, and ensuing relevance for the practice of international marketing.

Our main result—a *light-skin shift* among Hollywood starring casts—is supported by various pieces of evidence and extensive robustness checks. Yet, an important question remains. To which extent did this *light-skin shift* pay-off for Hollywood studios? Considering

that box-office performance in China continues to be a hit-or-miss for Hollywood productions,⁵⁹ there is a real possibility that studios may not yet fully grasp the determinants of success in that market. Data limitations and multiple layers of endogeneity make this a difficult empirical question, however. We must therefore leave this question for future research.

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Endnotes

¹ Walls and McKenzie (2012) provide evidence that suggests that the Hollywood industry has started to increasingly cater to foreign preferences. However, the foreign markets that they consider do not include emerging markets.

² After tripling total box office revenues in a five-year period, China became, in 2015, the second largest market (after the United States and ahead of the United Kingdom), accounting for 18% of the approximate \$40B global box-office revenues (Motion Picture Association of America 2015). The market, which already tops the international list in terms of number of screens (Lin 2016), is projected to displace the United States in the top of the box-office ranking by the turn of the decade (Kokas 2017).

³ Rosen (2015) cites examples suggesting that Hollywood has begun to progressively avoid negative representations thereof.

⁴ It is important to highlight that coloristic preferences are not exclusive to the Chinese culture nor to Asia in general. In fact, evidence that coloristic preferences shape socioeconomic and cultural outcomes is available from around the globe—including societies with predominantly dark-skinned populations. Several such cases are described in Hall (2012). The World Health Organization (2011) further notes that the consumption of potentially hazardous skin whitening cosmetics is prevalent around the world. Our focus on China stems from the conflux of factors that make it an interesting subject of study, namely, this nation's economic prowess, the marked presence of coloristic preferences therein, and its recent foreign film importation policy change.

⁵ We credit the associate editor for highlighting this threat.

⁶ We thank an anonymous referee for identifying this possibility and suggesting an empirical test.

⁷ Mendelson (2017a) also references "Warcraft" (2016) as an example of the same point.

⁸ Evidence has linked coloristic preferences with outcomes such as years of schooling (Loury 2009) and overall educational attainment (Ryabov 2016), assortment in the marriage market (Hamilton et al. 2009), access to financing (Jenq et al. 2015), and lengths of prison sentences (Viglione et al. 2011, King and Johnson 2016). Kreisman and Rangel (2015) provide consistent evidence from the labor market by examining earning gaps and tenure.

⁹ In Chinese culture, jade symbolizes nobility, perfection, and immortality, among other virtues, and it is considered the most valuable of all precious stones.

¹⁰ The Economist (2016) reports that "China today is extraordinarily homogeneous. It sustains that by remaining almost entirely closed to new entrants except by birth." This statement is in part supported by recent statistics for naturalized citizens: while the United States, Britain, France, and Russia naturalized between 0.1% and 0.4% of their respective populations, China has naturalized 0.0001% in total (i.e., across years).

¹¹ By contrast, coloristic differentiation in African societies is portrayed as operating through lighter shades of black (Lewis et al. 2013).

¹² Forbes (Sin 2016) reports that, because of its initial popularity, the price of the selfie-enhancing Exilim TR Casio camera rose from an initial US\$249 to US\$800–\$1000 shortly after its release. Quartz (2016) reports that selfie-enhancing Meitu app had over 900 million users by March 2016.

¹³ To this effect, Lynch (2016) states that, "nothing says Western values quite like a Hollywood movie [...] In China, films have long been an important propaganda tool to promote socialist values and the hegemony of the Chinese Communist Party ("CCP").

¹⁴ An alternative route of entry entails sidestepping the "foreign film" label by engaging in coproductions with Chinese firms. Although there are no known restrictions for this entry mode, there neither is a clear definition of what constitutes a legitimate coproduction in the eyes of the regulator, nor reassurance that all coproduced films will be allowed in. In fact, in our data, about 45% of coproductions with Chinese firms do not enter the market.

¹⁵ An additional economic incentive for the importation of popular films stems from the reconfiguration of Chinese retail commerce around shopping malls, whose operators have favored theater chains as tenants to foster footfall (Financial Times 2016).

¹⁶ Perhaps the most salient example of studios' strive to earn the SAPPRT's goodwill corresponds to "The Martian" (2015), where a mission of the Chinese National Space Administration saves the day for the lead character and NASA (Hoad 2015).

¹⁷ The IMDb popularity voting system is designed to minimize the extent of manipulation, for example, by limiting voting rights to registered users and allowing these to issue a single vote for each film. The selected threshold was 500 votes. Parsing through titles with fewer votes revealed that many such films are notoriously less impactful. Moreover, for these, design characteristics that are important for our analysis are often missing.

¹⁸ The "other" category includes genres that are less frequent in the data. These are western, musical, biography, history, and sport.

¹⁹ The system awards the following ratings: PG for films suitable for audiences aged 7 and older; PG-13 for audiences aged 13 and older; and R for restricted audiences. It has been argued that these ratings can, by themselves, impact overall appeal and commercial performance of a film, even after holding content constant (Pálsson et al. 2013). The system has been criticized based on an alleged inconsistency, whereby films containing scenes of comparable nature are awarded different ratings (Pomerantz 2010). Consequently, they may be subject to a degree of uncertainty from the perspective of producers.

²⁰ Although proxying for a film's quality through awards is problematic in some respects, previous research has made this connection and provided supporting evidence (e.g., Nelson et al. 2001, Ginsburgh 2003, Deuchert et al. 2005).

²¹ We consider the following major awards: Oscars (Academy Awards), Golden Globes, BAFTA Awards, Golden Lion (Venice Film Festival), Palme d'Or (Cannes International Film Festival), Grand Jury Prize (Sundance Film Festival), The Golden Bear (Berlin International Film Festival), The Golden Leopard (Locarno International Film Festival), and Filmfare Awards.

²² In addition, promotional budgets tend to be proportional to production budgets (Vogel 2014).

²³In practice, this codification assumes that missing budgets lie somewhere in the bottom 75% of each distribution. To investigate the validity of this assumption, we resorted to IMDb popularity votes. In particular, if we found that budget information tends to be missing for very popular films, our assumption would not be supported by the data. Statistics presented in the online appendix suggest the opposite: films with missing budget information are typically associated with a much smaller number of IMDb popularity votes than those for which budget data is available.

²⁴These studios are Disney, Fox, Paramount, Sony, Universal, and Warner Bros.

²⁵As defined, CHINESECOPROD accounts for coproductions with Chinese companies or the inclusion of scenes shot in Chinese territory. This variable is constructed primarily based on shooting location and country of origin data for involved firms (available from IMDb Pro), but supplemented with films' stated country of origin. That is, CHINESECOPROD = 1 if one of the film's declared origination countries is China.

²⁶We identify these in the data through the following markers: festival release, limited release, screening, premiers, and Internet release.

²⁷That is, some of the films that entered China in 2009 may correspond to films released in the United States years prior. This censoring will not affect our later econometric results, as estimated models include year fixed effects and primarily rely on cross-sectional film design variation.

²⁸In the online appendix we present a sample film to illustrate the retrieval of starring casts, and the correspondence of this list with the design of promotional material.

²⁹MTurk (Amazon Mechanical Turk) is a crowdsourcing online marketplace, where task requesters post simple human intelligence tasks performed remotely by workers. To minimize cultural variation, we selected U.S.-based coders only.

³⁰Standard checks (variance inflation, condition number) do not point to multicollinearity issues.

³¹Specifically, an expert on the Chinese film market states that "Humor is notorious for not translating as well, say, action or thrillers. Some genres cross boundaries with relative ease, but humor is much more difficult" (Andress 2016).

³²"Films are forbidden to have the following contents: (...) publicizing obscenity or superstitions or playing up violence" (People's Republic of China 1996, Chapter I, Article 24.5).

³³These may increase overall interest among audiences among others, by generating word of mouth, or signaling quality (Ginsburgh 2003).

³⁴Furthermore, note the correlations between specifications estimated on the same subsample are also generally high. This suggests that non fully controllable characteristics do not materially condition the likelihood of entry.

³⁵Our reasoning is based on the possible presence of risk aversion on the part of producers. Because entry into China cannot be guaranteed, casting decisions $Y^* | X$ are made in the context of market uncertainty. Because the costs implied by this type of risk are relatively more important, the lower $\Pr(\text{CHINAENTRY} | X)$ is, the latter's impact on casting decisions should be disproportionately larger at larger values.

³⁶This strategy—pairing a DiD specification with a continuous treatment intensity measure computed on predata—has previously been used to analyze natural experiments by Acemoglu et al. (2004), Finkelstein (2007), Lakdawalla et al. (2013), and Dranove et al. (2017), among others.

³⁷For instance, since the Affordable Care Act became effective in 2010, there has been a steadily declining trend in the rates of uninsured young adults (McMorrow et al. 2015), increasing the propensity of this population segment to quit their jobs and pursue independent professional endeavors. In fact, some evidence (Bailey 2017,

Blumberg et al. 2014) suggests that, by reducing the dependency employer-based health insurance, this trend may have had a positive impact on rates of entrepreneurship. Therefore, to the extent that the decline of uninsurance rates varied across individuals of different races, it is possible to conceive an impact on the relative supply of light- and dark-skinned actors. Furthermore, insofar declining uninsurance rates increased disposable income for some segments more than others, studios may have adjusted design characteristics (including casting) to better compete for these audiences.

³⁸Estimating the model on 2009–2013 data only, a test for the joint significance of these coefficients yields p -values of 0.96, 0.49, and 0.57, respectively, for DEXPOSURE, CEXPOSURE1, and CEXPOSURE2.

³⁹We generated 1,000 pseudosamples, resampling (with replacement) in each case the same number of films released in 2009–2012. Using each of these pseudosamples, we reestimated the model of Table 2, column 1, and constructed the exposure metrics for all films. We then took each of these to the full sample and reestimated specification (1).

⁴⁰We added the 2009–2012 and 2013–2015 lines to illustrate the robustness of our conclusion.

⁴¹Eliashberg et al. (2014) get around this by constructing a sample from 300 publicly available scripts.

⁴²Plots are written by IMDb users. Although IMDb does not clarify the source of films' synopsis, it is likely that they are provided by the producers.

⁴³We applied three filters. First, we removed punctuation and "stop words," which are common words that usually do not add meaning to the text (e.g., "a," "and," "is," "the"). Second, we applied a "stemming" procedure, aimed at distilling a base from derivatives and inflectional forms. For example, after the stemming procedure is applied, "cars," "car's," and "cars'" are all replaced by "car." Last, we removed personal names. In preliminary runs, we found that personal names artificially inflated measured similarity between films. We removed them using the list of each film's characters and a library of personal names.

⁴⁴Three of the 10 most similar pairs correspond to sequels, while among most of the remaining pairs, both films develop the same, distinctive topic (e.g., rodeo, vampires, witch hunts).

⁴⁵For example, the storylines of many thrillers revolve around a crime, while many comedies are inspired by stories about college.

⁴⁶Specifically, the results do not change when we also include $\|X_{ij}^G\|$ and $\|X_{ij}^C\|$.

⁴⁷In the online appendix we present the resulting distribution of this proxy.

⁴⁸Actors in the decile of highest popularity play an average of 4.8 roles; those in the next decile, 3.1; those in the decile that follows, 2.3. This monotonic progression continues to hold as we move down in the rank of measured fame. The average number of roles played by actors in the lowest-popularity decile is 1.1. These results also hold when we consider actors' mean FAME in the sample.

⁴⁹To construct PREVCHINAROLES we use casting data for films released between 2005–2015, and that satisfy the same popularity criteria as in our main sample.

⁵⁰We add one to the numerator because PREVCHINAROLES equals zero in the majority of cases.

⁵¹The number of observations in panel B (D) is smaller than that in panel A (C) because of the lower frequency of actors in the darkest skin-color category; the dependent variable is sometimes perfectly predicted by some combinations of X .

⁵²In Mainland China, this is about 92% (People's Republic of China 2010); in Taiwan, more than 95% (Department of Information Services, Executive Yuan 2014); in Hong Kong, about 94% (Population Census Office 2011). For comparison with other countries in which the

Han ethnicity has a significant presence, these percentages are 76% in Singapore (Department of Information Services, Executive Yuan 2014) and 23% in Malaysia (Department of Statistics Malaysia 2016).

⁵³Taiwan first lifted the importation quota and relaxed print control during the 1980s (Wang 2003), while other restrictions were dropped when Taiwan joined the WTO in 2001. In 2011, 97% of box-office revenues in this market were generated by foreign movies (Jaffe 2011). Hong Kong, on the other hand, has historically displayed large degrees of trade openness and become a theatrical hub for the region. (Current U.S. official reports do not mention restrictions for entry into this market. See http://2016.export.gov/hongkong/eg_hk_027494.asp.) In 2016, over 80% of all films screened in Hong Kong were foreign (HKTDC Research 2017).

⁵⁴We identified films released in Hong Kong and Taiwan as previously done for Mainland China. That is, we excluded limited and festival releases, and others that do not entail broad access by general audiences.

⁵⁵Because the focus of this analysis is entry (as opposed to design), we also include nonfully controllable design characteristics (MPAA ratings, awards), and define POST as $1[t \geq 2013]$.

⁵⁶For example, the coefficient of SHARELIGHT is forced to rationalize Mainland China entry outcomes for low-budget horror films, which tend to not enter Mainland China for reasons other than the potential coloristic bias of authorities (Martinsen 2010).

⁵⁷As before, because the focus is entry (as opposed to design), we define POST = $1[t \geq 2013]$.

⁵⁸See <https://wikileaks.org/sony/emails/emailid/62426>.

⁵⁹There are several examples of films that have dramatically overperformed or underperformed in China relative to prerelease expectations. For example, Mendelson (2017b) claims that “Arthur: Legend of the Sword” (2017) and “Power Rangers” (2017) “got their butts kicked” in their opening weekends in China, further stating that the case of Power Rangers was a “real tragedy.” By contrast, the unexpected China success of “Pacific Rim” (2013) has been pointed by Lee (2016) as the main factor behind its upcoming sequel. The same article states that in 2013, this seemed an “unlikely proposition.”

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