Actors' Facial Similarity and its Impact on U.S. Movies' Box-Office Performance in East and South-East Asia

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Purpose

Anecdotal evidence suggests that casting actors with similar facial features in a movie can pose challenges in foreign markets, hindering the audience’s ability to recognize and remember characters. Extending developments in the literature on the *cross-race effect*, we hypothesize that facial similarity – the extent to which the actors starring in a movie share similar facial features – will reduce the country-level box-office performance of U.S. movies in East and South-East Asia (ESEA) countries.

Design

We assembled data from various secondary data sources on U.S. non-animation movies (2012-2021) and their releases in ESEA countries. Combining data resulted in a cross-section of 2,616 movie-country observations.

Findings

Actors’ facial similarity in a U.S. movie’s cast reduces its box-office performance in ESEA countries. This effect is weakened as immigration in the country, Internet penetration in the country, and star power increase and strengthened as cast size increases.

Originality

This first study on the effects of cast’s facial similarity on box-office performance represents a novel extension to the growing literature on the antecedents of movies’ box-office performance by being at the intersection of the two literature streams on (1) the box-office effects of cast characteristics and (2) the antecedents, in general, of box-office performance in the ESEA region.

Keywords: Actors, Facial Similarity, International Box-office, East Asia, South-East Asia, *Cross-Race Effect*.

1 Introduction

Dax Shepard and Zach Braff, Minka Kelly and Leighton Meester, Amy Adams and Isla Fisher – these are just some examples of lookalikes in Hollywood that frequently spark discussions on the Internet. Hollywood studios and actors seem to be attuned to this ongoing conversation. As an example, actor Emma Mackey recently acknowledged the frequent comparisons to Margot Robbie and even declared to TotalFilm that their facial similarity played a role into her selection to star alongside Robbie in the movie Barbie (Maytum 2022). While the decision to cast Mackey alongside Robbie in Barbie has generated excitement online (Kemp 2022), anecdotal evidence suggests that casting actors with similar facial features in a movie can pose challenges, particularly in foreign markets, as it may diminish the audience's ability to recognize and remember characters. For instance, audiences were confused by Leonardo DiCaprio and Matt Damon starring together in The Departed (Costandi 2011) and by Samuel L. Jackson and Laurence Fishburne starring together in School Daze (Swarns 2015).

While the phenomenon of lookalikes in Hollywood has received extensive attention in the press, it has yet to be explored in the marketing literature. Against this backdrop, in this research we delve into the effect of facial similarity in a movie's cast – the extent to which the actors starring in a movie share similar facial features – on the country-level box-office performance of U.S. movies in East and South-East Asia (ESEA) countries (2012-2021).

In formulating the hypotheses, we build on the so-called *cross-race effect* – one's inclination to more easily recognize and remember faces that belong to their own *racial* group (Feingold 1914). Despite humans' proficiency in processing faces, in fact, there exists significant variation in the types of faces that individuals encounter in their daily lives. People generally have less extensive contact with individuals who belong to *cross-race* groups, leading to a tendency to better recognize and remember members of their own *racial* group (Meissner and Brigham 2001).

Extending developments in the literature on the *cross-race effect,* we expect that an increase in facial similarity in a movie's cast will reduce U.S. movies' box-office performance in ESEA countries. This effect is to be attributed, we argue, to a reduction in the audience's processing fluency, the subjective feeling of ease associated with mental processing (Graf, Mayer, and Landwehr 2018). Specifically, we predict that ESEA audiences, influenced by the *cross-race effect*, will experience lower processing fluency when encountering movies starring actors with similar facial features. Our findings support this hypothesis, demonstrating that facial similarity in the cast indeed reduces the box-office performance of U.S. movies in ESEA countries.

We also investigate whether and how this effect is moderated by two country characteristics – immigration and Internet penetration – and two movie characteristics – cast size and star power. The choice of moderators is driven by the need for thorough theoretical testing and by their relevance for business practice. Consistent with our theorizing, the negative effect of actors' facial similarity on the box-office performance of U.S. movies in ESEA countries is weakened as immigration in the country, Internet penetration in the country, and star power increase and strengthened as cast size increases.

We focus on the ESEA region for two reasons. First, the ESEA region comprises numerous relevant markets for Hollywood studios (Hermosilla, Gutierrez-Navratil, and Rodriguez-Prieto 2018; Wu et al. 2022). In 2022, three countries in this region – China, Japan, and South Korea – ranked among the global top 10 in terms of box-office revenue (Gower Street Analytics 2023). The relevance of these markets is also evident as the expectations of Chinese audiences and authorities have recently prompted modifications to Hollywood movies. For instance, in the trailer of Top Gun Maverick (2022), the jacket previously wore by Tom Cruise and adorned with Japanese and Taiwanese flags was altered to feature arbitrary symbols[1] (Cheung 2022). Second, our focus on the ESEA region stems from the expectation that the *cross-race effect* will be more pronounced in this region due to the low representation of Asian actors in U.S. movies (Hunt and Ramón 2023), with only 2.3% of movie leads currently being of Asian descent.

The contributions of this study are threefold.

First, from a theoretical standpoint, this study is the first in the marketing literature to examine the impact of facial similarity in a movie's cast, in general, and on box-office performance, in particular. In doing so, the study represents a novel extension to the growing literature on the antecedents of movies' box-office performance by being at the intersection of the two literature streams on (1) the box-office effects of cast characteristics and (2) the antecedents, in general, of box-office performance in the ESEA region. The study extends the literature by showing that casting facially similar actors in a movie diminishes its box-office performance in the ESEA region.

Second, again from a theoretical standpoint, the findings contribute to the literature on the *cross-race effect* by suggesting its boundary conditions, as the negative effect of facial similarity on box-office performance is weakened as immigration, Internet penetration, and star power increase and strengthened as cast size increases. In doing so, this effort offers a nuanced examination of the determinants of movies' international box-office performance by shedding light on the intricate interplay between contextual and movie-level variables.

Third, from a practical standpoint, by highlighting the importance of considering international audiences during the movie production stage, this research holds significant implications for Hollywood studios. Given the reliance of Hollywood on global markets, in general, and ESEA markets, in particular, understanding how their decisions, including on casts, influence box-office performance becomes paramount for studios.

2. Theoretical Background

We extend the growing literature on movies' box-office performance, in general, and, in particular, the narrower literatures on (1) the box-office effects of cast characteristics and (2) the antecedents of box-office performance in the ESEA region.

2.1 Cast Characteristics and Box-Office Performance

There is a growing literature on the box-office effects of cast characteristics. This literature has thus far mainly focused on star power and *racial* diversity (see Table I).

----- Table I -----

On the one hand, casting stars has been shown to influence box-office performance either directly (Basuroy, Chatterjee, and Ravid 2003; Elberse 2007) or indirectly, by affecting stakeholder involvement and financial investments (Liu et al. 2014) and buzz (Karniouchina 2011). On the other hand, the *racial* and gender diversity of the cast also has been shown to impact box-office performance (Giannetti and Chen 2023; Kuppuswamy and Younkin 2020).

We note here that, despite the phenomenon having received extensive attention in the press in recent years, none of these papers has investigated the effect of facial similarity in a movie's cast, the focus of our work, nor focused explicitly on the ESEA region.

2.2 Antecedents of Box-Office Performance in the ESEA Region

The antecedents of box-office performance in the ESEA region have so far received limited attention in the marketing literature (see Table II).

----- Table II -----

According to studies in this area, genres can differently impact box-office performance in ESEA countries (Chiu et al. 2019; Lee 2008, 2009; Moon et al. 2015). Further, Academy Awards nominations may influence box-office performance, with non-drama (drama) award nominations increasing (decreasing) box-office performance (Lee

2009). Further, Gao et al. (2020) find that, contingent upon various factors, higher similarity and informativeness of title translations increase box-office performance in China. Keh et al. (2015) and Chiu et al. (2019) show that online reviews and electronic word-of-mouth (eWOM) affect purchase intention and box-office performance in ESEA countries, respectively. Last, Wu et al. (2022) focus on the Chinese government's import decisions. Government administrative trade interventions regarding release timing limit the impact of Hollywood movies, creating implicit trade barriers.

In sum, the literature on the antecedents of box-office performance in the ESEA region has largely neglected the role of cast characteristics, in general, and facial similarity, in particular, in driving box-office performance.

2.3 Cross-Race Effect

The *cross-race effect*, first introduced by Feingold in 1914, posits that individuals have an inclination to more easily recognize and remember faces that belong to their own *racial* group (Malpass and Kravitz 1969). This effect has been found to apply to numerous populations (Young et al. 2012) and is considered one of the most replicable findings in the social psychological literature (Adams et al. 2010). Testifying to its relevance, the *cross-race effect* has been blamed for prejudicial outcomes in the U.S. legal system, leading to wrongful convictions of individuals from *racial* minority groups (Swarns 2015).

Several explanations have been proposed for the *cross-race effect*. One of the most common explanations for the *cross-race effect* is the lack of exposure to individuals from other *races*, which leads to a lack of expertise in processing and recognizing *cross-race* faces (Rhodes et al. 1989; Sangrigoli and De Schonen 2004). Supporting this explanation, the *cross-race effect* diminishes when exposure to *cross-race* faces increases either in childhood (Sangrigoli et al. 2005) or adulthood (Hancock and Rhodes 2008), sometimes even resulting in a recognition advantage for *cross-race* faces.

We note here that, all throughout this research, we often mention "*races*" and the "*cross-race effect*". We are mindful that *race* is a social construct rather than a biologically determined characteristic. The concept of *race* emerged as a socially-constructed, oversimplified way of categorizing people based on perceived physical attributes such as skin color, hair texture, and facial features (Pappas 2013). Consistent with this understanding and with the above-mentioned literature on the *cross-race effect*, we refer to the *cross-race effect* as a socially (vs. biologically) determined phenomenon, driven by reduced exposure to *cross-race* faces. Hence, in the words of Malpass, we "will continue to refer to this as the *Cross-Race Effect*, and you will hopefully understand that when *we* do so *we* mean it with quotation marks around it" (1996, p. 9).

2.3.1 Main Effect

The issue of underrepresentation of minorities in Hollywood is a topic of intense debate (Chow 2016). In response to public demands for increased representation, 2020 marked a significant milestone as *racial* minority actors surpassed proportionate representation in Hollywood movies (Hunt and Ramón 2023). However, despite their recent achievements in Hollywood, including at the 2023 Academy Awards, the representation of Asian actors remains inadequate. In 2022, Asian actors constituted only 2.3% of movie leads (Hunt and Ramón 2023).

Given this context, we anticipate that ESEA audiences will experience a considerable *cross-race effect* when exposed to movies that predominantly feature non-Asian actors. Drawing from the literature on the *cross-race effect* (Malpass and Kravitz 1969; Meissner and Brigham 2001), in fact, we know that individuals are better equipped to recognize and remember faces from their own *racial* group.

Against this backdrop, we expect that the *cross-race effect* experienced by ESEA audiences will likely be exacerbated when a Hollywood movie's cast exhibits high facial similarity. We argue that such similarity can diminish the processing fluency of ESEA audiences, reducing their overall ease of engaging with the movie. Supporting this argument, studies have shown that reduced processing fluency diminishes liking (King and Janiszewski 2011; Lee and Labroo 2004) and aesthetic pleasure in the context of drawings, abstract paintings, and pictures (Reber, Schwarz, and Winkielman 2004).

By integrating these arguments, we hypothesize that higher facial similarity in a U.S. movie's cast will lead to worsened responses from ESEA audiences and, consequently, reduce box-office performance. Thus, we offer:

H_1. *Facial similarity in a U.S. movie's cast will reduce the movie's box-office performance in ESEA countries.*

2.3.2 Moderation Effects

We propose that the negative effect of actors' facial similarity on U.S. movies' box-office performance in ESEA countries (H_1) is moderated by two country characteristics – immigration and Internet penetration – and two movie characteristics – cast size and star power. The country-level variables were drawn from the literature on the *cross-race effect*, which has shown that both direct (immigration) and indirect (Internet) exposure to *cross-race* faces can mitigate the *cross-race effect*. The movie-level variables were selected upon inspection of the relevant marketing literature and based on managerial relevance. Specifically, cast size and star power are managerially actionable variables which may affect the audience's ability to remember and recognize actors and characters.

Immigration A well-documented intervention to mitigate the *cross-race effect* is to enhance perceptual expertise (Meissner and Brigham 2001) in processing *cross-race* faces through increased exposure to *racial* diversity. When people are exposed to individuals of diverse *races*, they develop greater proficiency in recognizing *cross-race* faces. For instance, adopted Korean children raised in Europe exhibit an advantage in recognizing European faces, which suggests a reversal of the *cross-race effect*, due to increased exposure to European faces compared to Asian faces (Sangrigoli et al. 2005). Immigration within a country may serve as a fundamental source of direct exposure to *racial* diversity. Studies show that the extent of the *cross-race effect* is reduced by contact with individuals from *racial* outgroups (Hancock and Rhodes 2008) as well as in *multiracial* populations (Bar-Haim et al. 2006; Chiroro and Valentine 1995).

Hence, we argue that, as immigration in a country increases, greater prior direct exposure to diversity will reduce the *cross-race effect*, increasing processing fluency and, in turn, weakening the negative effect of facial similarity on box-office performance. Thus, we offer:

H_2: *The negative effect of facial similarity in a U.S. movie's cast on box-office performance in an ESEA country is weakened as immigration in the country increases.*

Internet Penetration As mentioned above, exposure to diversity mitigates the *cross-race effect*. In addition to direct exposure to diversity through living in a diverse social context, indirect exposure can also mitigate the *cross-race effect*. As an example, perceptual expertise gained through laboratory training programs improves *cross-race* recognition (Tanaka and Pierce 2009). Thus, both long-term developmental experience such as that acquired in a diverse social context and brief, experimentally induced *cross-race* experience can improve *cross-race* recognition. We argue that Internet penetration in one's country is a fundamental source of indirect exposure to diversity. Internet has, in fact, exponentially increased the amount of diversity to which we are exposed (European Commission 2020) while social media, in particular, enables cross-cultural interaction and exposure to diverse content (Hermann, Eisend, and Bayón 2020).

Hence, we argue that, as Internet penetration in a country increases, greater prior indirect exposure to diversity will reduce the *cross-race effect*, increasing processing fluency and, in turn, weakening the negative effect of facial similarity on box-office performance. Thus, we offer:

H_3: *The negative effect of facial similarity in a U.S. movie's cast on box-office performance in an ESEA country is weakened as Internet penetration in the country increases.*

Cast Size According to the literature, simpler stimuli require less processing capacity compared to complex stimuli (Mayer and Landwehr 2018). Consequently, complexity in a movie, the amount of information the movie contains (Garner 1974), may exacerbate the negative effect of facial similarity on box-office performance. We argue that cast size – the number of actors starring in a movie – plays a crucial role in determining the movie's complexity. Relatedly, Paulich and Kumar (2021) note that a larger number of characters in a movie, a variable which is highly correlated with cast size, may increase cognitive load, introduce confusion, and divert attention away from the movie's central narrative.

Hence, we argue that, as cast size increases, greater complexity will increase the audience's difficulty in remembering and recognizing characters, reducing processing fluency and, in turn, strengthening the negative effect of facial similarity on box-office performance. Thus, we offer:

H_4: *The negative effect of facial similarity in a U.S. movie's cast on box-office performance in ESEA countries is strengthened as cast size increases.*

Star Power Star power, which is determined by actors' past artistic and commercial success, is considered an important driver of box-office performance (Elberse 2007). Due to their achievements, stars are familiar to audiences (Griffith et al. 2017), who have been exposed to them on multiple occasions. Additionally, stars may generate substantial media coverage, further enhancing their familiarity and creating buzz around their movies (Karniouchina 2011). Increased exposure to stimuli enhances processing fluency (Landwehr, Golla, and Reber 2017). Hence, despite the *cross-race effect*, as the star power of the actors featured in a movie increases, ESEA audiences will be better equipped to remember and recognize them as well as their characters.

Hence, we argue that, as star power increases, greater past exposure to actors will decrease the audience's difficulty in remembering and recognizing characters, increasing processing fluency and, in turn, weakening the negative effect of facial similarity on box-office performance. Thus, we offer:

H_5: *The negative effect of facial similarity in a U.S. movie's cast on box-office performance in ESEA countries is weakened as star power increases*.

Figure I outlines the conceptual framework.

----- Figure I -----

3. Data

We collected data from the-numbers (https://www.the-numbers.com/) on U.S. non-animation movies (2012-2021; the latest worldwide release date in the sample is September 1st, 2021) and their releases in 13 ESEA countries[2].

Starting from our sample of movies and using data from the-numbers[3], we singled out all the principal cast members, namely, the leading actors. These are the actors serving as protagonists and responsible for conveying the primary storyline in the movie. For movies with no clearly identifiable protagonists, we selected lead ensemble members instead. For each actor, we then downloaded a shot from IMDb (https://www.imdb.com/). We used face analysis AI tools[4], Kairos and Face++, to determine, for each actor, the *racial* group (Asian, Black, Hispanic, or White) and gender and compute facial similarity. We used Kairos (https://kairos.com/), a face and diversity recognition algorithm, to determine the *race* and gender of each actor (Kuppuswamy and Younkin 2020). We assigned actors to the *race* and gender for which Kairos generated the highest probability. We then used the Face++'s face-comparison API (https://faceplusplus.com) to calculate facial similarity for each pair of actors belonging to the same *racial* group and gender. Face++ is a state-of-the-art commercial algorithm in face comparison, often deployed in online banking to authenticate customers' identities, and has been shown to achieve an accuracy of 99.5% in recognizing the same face (Zhou et al. 2015) on the benchmark face database Labeled Faces in the Wild (LFW; Huang et al. 2008). For each pair of actors, Face++ generates a score ranging between 0-100, indicating their facial similarity. The higher the score is, the more similar the two faces. We set facial similarity to 0 when actors belong to different *racial* groups and/or genders. Although an approximation, we argue that this approach is reasonable in that it allows to cut down on the computing resources required by the algorithm, without compromising reliability. We examined a sample of facial similarity scores to check for their validity. Testifying to the validity of the algorithm, in the Appendix, we report pairs of lookalikes often covered in celebrity news (Lane and Yagoda 2022) with the corresponding facial similarity score.

Our key independent variable is facial similarity in the movie's cast – the average facial similarity of each pair of principal cast members starring in the movie. The variable takes on value 0, among others, when the movie has only one principal cast member.

We measure immigration as the percentage of the population constituted by immigrants, which is available from the World Bank[5]. We measure Internet penetration as the percentage of the population which uses the Internet, which is again available from the World Bank[6]. We measure cast size as the number of principal cast members starring in the movie. Last, we measure star power as the average movie gross in USD for each principal cast member, averaged across all principal cast members, prior to the movie's worldwide release date. Our dependent variable is country-level box-office performance, measured as revenues in USD for the movie in the country. We include control variables in the model used to test the hypotheses.

We provide the variables (including control variables) and measures in Table III and the descriptives in Table IV.

----- Tables III and IV -----

Combining all data (after excluding observations with missing values) resulted in 2,616 movie-country observations (659 movies; 13 countries; not all movies are released in all countries).

4. Estimation

We estimate the following equation:

$$Box-Office\ Performance_{ic} = \beta_0 + \beta_1 Facial\ Similarity_i + \beta_2 Facial\ Similarity_i \times Immigration_c + \beta_3 Facial\ Similarity_i \times Internet\ Penetration_c + \beta_4 Facial\ Similarity_i \times Cast\ Size_i + \beta_5 Facial\ Similarity_i \times Star\ Power_i + \beta_6 Immigration_c + \beta_7 Internet\ Penetration_c + \beta_8 Cast\ Size_i + \beta_9 Star\ Power_i + \beta_{10} Budget_i + \beta_{11} Director\ Power_i + \beta_{12} Distribution\ Intensity_{ic} + \beta_{13} Competitive\ Intensity_{ic} + \beta_{14} Critic\ Review\ Score_i + \beta_{15} Academy\ Award_i + \beta_{16} General\ Audience\ Unsuitability_i + \beta_{17} Sequel_i + \beta_{18} Remake_i + \beta_{19} Spin-off_i + \beta_{20} Previous\ Launches_{ic} + \beta_{21} Time-lag_{ic} + \beta_{22} Proportion\ of\ Asian\ Actors_i + \beta_{23} Proportion\ of\ Black\ Actors_i + \beta_{24} Proportion\ of\ Hispanic\ Actors_i + \beta_{25} Proportion\ of\ Female\ Actors_i + \beta_{26} Diversity_i + \beta_{27} Major\ Studio_i + + \sum_{n=28}^{34} \beta_n Genre_i + \sum_{n=35}^{43} \beta_n Year_{ic} + \sum_{n=44}^{55} \beta_n Country_c + \varepsilon_{ic} \quad (1)$$

where βs are the parameters to be estimated, subscripts i represent movies, subscripts c represent countries, and ε_{ic}s are the error terms. The model includes genre[7], year of release, and country indicators. Two potential concerns are endogeneity and sample selection. We address them in robustness checks adopting a Gaussian Copula approach and a Heckman Sample Selection Model, respectively. The results are generally robust, as we show later.

5. Results

In Column 1, Table V, we report the results obtained running the model at equation (1) without the key independent variable, i.e., facial similarity, and the interactions (R^2 = 69%). In Column 2, we report the results without the interactions (R^2 = 69%). Facial similarity reduces box-office performance (b = -0.004, $p < 0.05$). In Column 3, we include the interactions (R^2 = 70%). In support of H_1, facial similarity reduces box-office performance (b = -0.03, $p < 0.01$). In support of H_2 and H_3, respectively, the negative effect of facial similarity on box-office performance is weakened as immigration (b = 0.0002, $p < 0.01$) and Internet penetration, marginally, (b = 0.0001, $p < 0.10$) increase. In support of H_4, the negative effect of facial similarity on box-office performance is strengthened as cast size increases (b = -0.003, $p < 0.05$). Last, in support of H_5, the negative effect of facial similarity on box-office performance is weakened as star power increases (b = 0.001, $p < 0.01$). The stepwise addition of facial similarity and the interaction terms successively decreases the Akaike Information Criterion (AIC), indicating that each model fits the data more closely. The estimates of the controls are generally consistent with expectations. Internet penetration (b = 0.02, $p < 0.01$), cast size (b = 0.04, $p < 0.05$), budget (b = 0.65, $p < 0.01$), distribution intensity, marginally, (b = 0.01, $p < 0.10$), critic review score (b = 0.01, $p < 0.01$), Academy Award (b = 0.75, $p < 0.05$), sequel (b = 0.50, $p < 0.01$), spin-off (b = 0.97, $p < 0.01$), previous releases, marginally, (b = 0.02, $p < 0.10$), proportions of Asian (b = 0.84, $p < 0.01$), Hispanic (b = 0.33, $p < 0.01$), and female actors (b = 0.16, $p < 0.05$), and major studio (b = 0.57, $p < 0.01$) all increase box-office performance. On the contrary, immigration (b = -0.12, $p < 0.05$), star power (b = -0.01, $p < 0.01$), competition, marginally, (b = -0.002, $p < 0.10$), and time-lag (b = -0.003, $p < 0.01$) reduce box-office performance. The apparently counterintuitive result for star power is to be explained with mean reversion (Karniouchina et al. 2023).

----- Table V -----

5.1 Robustness Checks

Endogeneity One potential problem is endogeneity from omitted variable bias as unobservable considerations may drive both cast's facial similarity and box-office performance. We determine the impact threshold for a confounding omitted variable (ITCV) for our focal predictor, facial similarity. The ITCV measures how strong the impact from an omitted variable would have to be in order to invalidate the inference of facial similarity (Frank 2000). Invalidating our estimate would require an omitted variable explaining 49.22% of the estimate, a threshold which assuages concerns about threats from omitted variable bias. Notwithstanding this, we cannot claim that facial similarity is uncorrelated with the error term. We address this issue adopting the Gaussian Copula (GC) approach (Park and Gupta 2012). This approach models the joint distribution of the potentially endogenous regressor, facial similarity, and the error term through a control function term. One requirement for the GC approach is that the endogenous regressor is not normally distributed. The non-normal distribution of facial similarity is confirmed by a Shapiro-Wilk test ($SW_{FacialSimilarity} = 0.93$, $p < 0.001$). The absolute skewness of facial similarity is above the threshold of 0.8 for samples larger than 1,000 ($Skewness_{FacialSimilarity} = 1.45$) (Becker, Proksch, and Ringle 2022). In Column 1, Table VI, we include the GC in the model. The GC is not significant. The results are robust. As an additional check, we addressed endogeneity concerns using an alternative approach (Petrin and Train 2010). We first regressed facial similarity for the focal movie on the average facial similarity of all other movies produced in the same year (using the whole set of movie-level controls), we then computed the residual and added it to the model used to test the hypotheses as a predictor. The results (Column 2, Table VI) are unchanged.

Sample Selection Observing the box-office performance of a movie in a country requires the movie to be released in that country. Hence, we ran a Heckman sample selection model to predict a movie's likelihood of being released in a country (Heckman 1979). Specifically, we ran a probit model regressing the probability of the movie being released in a country on our set of control variables (excluding distribution and competitive intensities, as this information is not available before release, and replacing the country-specific year of release indicators with year of worldwide release indicators). We use, as an exclusion variable, the average number of releases for movies produced in the same year as the focal movie. The variable is significantly correlated with the probability of the movie being released in a country ($p < 0.01$). We compute the Inverse Mills Ratio (IMR) and add it in the model used to test the hypotheses. The results (Column 3, Table VI) are generally robust, although the interaction of facial similarity and Internet penetration becomes insignificant and the interaction of facial similarity and cast size becomes only marginally significant.

Alternative Measure for Facial Similarity We re-ran the model using the highest (vs. average) facial similarity in the movie's cast as an independent variable (mean = 24.00, std. dev. = 27.08, winsorized), as two highly similar actors may suffice to reduce processing fluency. The results (Column 4, Table VI) are generally robust, although the interaction of facial similarity and Internet penetration becomes significant and the interaction of facial similarity and cast size becomes only marginally significant, reasonably.

No Asian Actors To allow for a cleaner test of hypotheses, we re-ran the model excluding all movies with at least one Asian actor, as we do not expect facial similarity across Asian actors to bear effects in the ESEA region. The results (Column 5, Table VI) are generally robust, although the interaction of facial similarity with cast size becomes insignificant.

No Movies with One Principal Cast Member Recall that facial similarity takes on value 0 for movies with only one principal cast member. Hence, we re-ran the model excluding all observations for movies with only one principal cast member (facial similarity in the new sample: mean = 12.76, std. dev. = 13.75, winsorized). The results (Column 6, Table VI) are generally robust, although the interaction of facial similarity and Internet penetration becomes significant and the interaction of facial similarity and cast size becomes only marginally significant.

Sampling Variations In two additional analyses, we checked the robustness of results to sampling variations, by dropping movies released in the first two (Column 7, Table VI) and the last two (available upon request) years of data, respectively. The results are generally consistent.

6. Discussion

This first study of the impact of actors' facial similarity on U.S. movies' country-level box-office performance in the ESEA region offers significant contributions to theory and practice.

6.1 Theoretical Contributions

From a theoretical perspective, the study extends the growing literature on movies' box-office performance, in general, and, in particular, the narrower literatures on (1) the box-office effects of cast characteristics (see Table I) and (2) the antecedents of box-office performance in the ESEA region (see Table II). On the one hand, while the literature on the box-office effects of cast characteristics has thus far mainly focused on star power (Basuroy et al. 2003; Elberse 2007) and diversity (Kuppuswamy and Younkin 2020), to the best of our knowledge, it has yet to investigate the effect of facial similarity in a movie's cast. On the other hand, the literature on the antecedents of box-office performance in the ESEA region (Gao et al. 2020; Moon et al. 2015) has largely neglected the role of cast characteristics, in general, and facial similarity, in particular, in driving box-office performance.

Against this backdrop, starting from a phenomenon that has received extensive attention in the press, the present study shows that casting facially similar actors is associated to reduced box-office performance in the ESEA region. While recent studies have highlighted the importance of cast's *racial* representation (Kuppuswamy and Younkin 2020; Giannetti and Chen 2023), this study moves one step forward by focusing on a different type of representation. The findings highlight how representation, as it pertains to facial features, can bear beneficial effects from a box-office perspective. The findings also contribute to the literature on the *cross-race effect* (Meissner and Brigham 2001) by clarifying its boundary conditions. Specifically, the negative effect of facial similarity on box-office performance is weakened by immigration, Internet penetration, and star power, and strengthened by cast size. The main and moderation effects support the intuition that facial similarity decreases processing fluency, resulting in negative responses from ESEA audiences. Taken together, the key takeaway is thus that, although casting easily discernible actors increases a movie's box-office performance in the ESEA region, this effect is contingent upon country- and movie-specific characteristics.

6.2 Managerial Implications

From a practical perspective, this research holds significant implications for Hollywood studios. The key finding emphasizes the importance of casting easily discernible actors to enhance box-office performance in the ESEA region. This contradicts the anecdotal evidence suggesting that studios intentionally cast facially similar actors in the same movie. Since facial similarity is not easily determined, one solution would be to cast highly discernible actors from different *racial* backgrounds and genders. This approach would have the added benefit of promoting more equitable opportunities for female actors and actors of underrepresented backgrounds. Interestingly, in our data, facial similarity is significantly higher in the female (vs. male) group ($p < 0.01$), across all *racial* groups, suggesting that Hollywood has a *type* which is considered camera-worthy, and that this is particularly true, not surprisingly, we add, for female actors. According to the insights from this research, studios should try to widen the scope of facial features that are considered camera-worthy, especially when it comes to female actors. Increasing heterogeneity would be particularly useful in those ESEA countries that are low on immigration and Internet penetration. This is because, we argue, both immigration, directly, and Internet penetration, indirectly, result in greater *cross-race* exposure and, in turn, reduce the extent of the *cross-race effect*. Studios should also exercise particular caution when their movie features relatively unknown actors or has a large cast as this could introduce confusion and divert attention away from the movie's central narrative, exacerbating the reduction in processing fluency caused by the *cross-race effect*.

Overall, the findings highlight the importance of considering international audiences during the movie production stage. Given the significant reliance of Hollywood on global markets, in general, and ESEA markets, in particular, studios should recognize the critical role that casting decisions play in connecting with international audiences. We contend that studios should take into account the concept of processing fluency when making these casting choices.

While the data for this study is specific to the movie industry, the findings have broader implications for other cultural products, including TV series. Further, the implications may potentially extend to other contexts, such as service provision.

6.3 Limitations

This study has limitations that provide avenues for future research. First, driven by relevance considerations, this research focuses solely on the ESEA region, warranting exploration of other regions as well. Second, the mechanism of reduced processing fluency is not empirically tested in this research, highlighting the need for future experimental research explicitly examining it. While the moderation effects indirectly support our proposed mechanism, we advance three alternative mechanisms which could explain the negative effect of facial similarity on box-office performance. Consumers may appreciate casts including a more heterogenous set of facial features, as this (1) increases representativeness and inclusivity, in line with the recent trends of body, in general, and face positivity, in particular (Madan et al. 2018), (2) better captures Asian beauty standards, which are different from Western beauty standards (Cunningham et al. 1995), (3) increases the probability that one or more actors are similar to consumers watching the movie, resulting in better responses (Byrne 1971). Third, while we use multiple methods to address the potential endogeneity of facial similarity, omitted variable bias cannot be ruled out with certainty. Follow-up experimental studies would therefore be a useful extension. Fourth, our data does not allow to assess whether the effect of facial similarity changes over time after the release of a movie. Future research addressing this limitation would therefore be useful. Last, the use of AI to classify actors and compute facial similarity scores introduces the possibility of inadvertent bias. This should be considered when interpreting the findings.

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Footnotes

[1] The two flags eventually reappeared in the movie's worldwide release.
[2] Cambodia, China, Hong Kong, Indonesia, Japan, Malaysia, Mongolia, Myanmar, Philippines, Singapore, South Korea, Thailand, and Vietnam. While Hong Kong is formally a special administrative region of China, for the sake of simplicity, in the paper we only refer to ESEA countries.
[3] The-numbers classifies actors based on movies' theatrical poster(s).
[4] After using Kairos, we used Face++, followed by a manual inspection, to double check *race* and gender allocations.
[5] https://data.worldbank.org/indicator/SM.POP.TOTL.ZS. When a country-year measure is missing, we replace it with the most recent available measure before that.
[6] https://data.worldbank.org/indicator/IT.NET.USER.ZS.
[7] Action, adventure, comedy, drama, horror, musical, thriller/suspense, or Western (reference group).

Figure I: Conceptual Framework

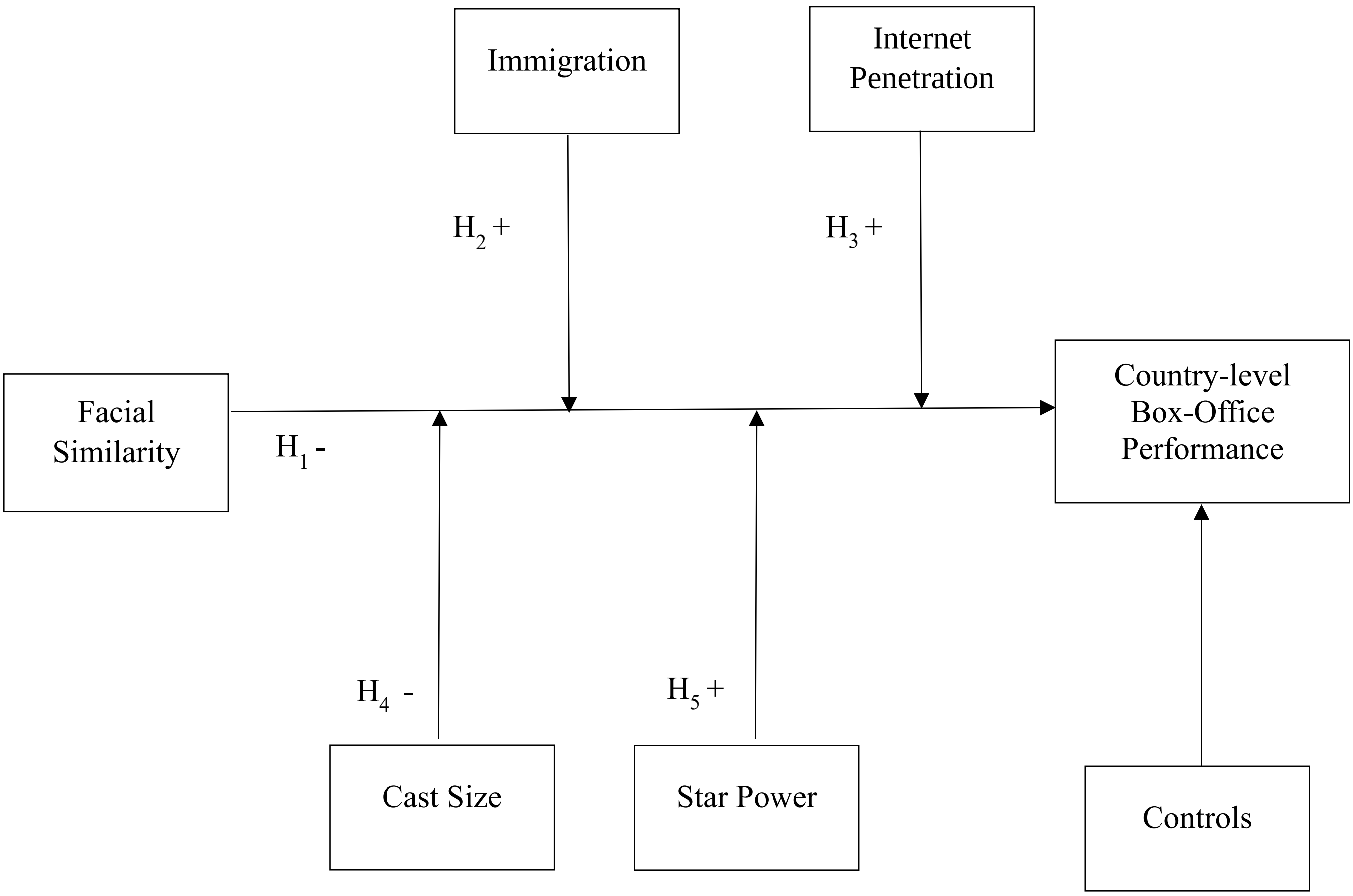

Table I: Cast Characteristics and Box-Office Performance

Paper	Time	ESEA Region	Facial Similarity	Focus	Outcome Variable
Basuroy et al. (2003)	1991-1993	No	No	Critical reviews, star power, budget	Weekly domestic box-office performance
Elberse (2007)	2001-2005	No	No	Star economic reputation, star artistic reputation	Expected box-office revenue (CARs, Event Study)
Giannetti and Chen (2023)	2012-2019	No	No	Cast *race* and gender	International country-level box-office performance
Karniouchina (2011)	2005	No	No	Star buzz, movie buzz	Opening-week and later-run domestic box-office performance
Kuppuswamy and Younkin (2020)	2011-2016	No	No	Cast *race*	Domestic box-office performance
Liu et al. (2014)	2000-2005	No	No	Star box-office success, star artistic success, genre fit	Opening-week number of viewers
This paper	*2012-2021*	*Yes*	*Yes*	*Facial Similarity*	*Country-level box-office performance in ESEA countries*

Table II: Antecedents of Box-office Performance in the ESEA Region

Paper	**Time**	**Countries**	**Cast Characteristics**	**Focus**	**Key Findings**
Chiu et al. (2019)	2010-2015	China (and U.S.)	No	eWOM, genre	Consumers in the U.S. and China display different reviewing behaviors. eWom variance affects the Chinese box-office while not affecting the U.S. one
Gao et al. (2020)	2011-2018	China	No	Brand name translation	Higher title similarity and informativeness enhance Chinese box-office performance. These effects are stronger for successful U.S. movies and movies with a significant cultural gap, respectively
Keh et al. (2015)	N/A (Survey)	China, Macau, the Philippines (and India)	No	Online ratings	Smaller ratings volumes and lower valence increase risk perceptions and decrease purchase intentions. The effects are amplified among conservative consumers
Lee (2008)	2002-2006	9 countries	No	U.S. box office performance, genre	Different movie genres are received differently in East Asia
Lee (2009)	2002-2007	9 countries	No	Academy Awards	Non-drama awards positively affect box-office performance, while drama awards negatively affect it. This negative relationship is worsened as cultural distance increases
Moon et al. (2015)	2007-2009	South Korea	No	Import vs. domestic, market awareness, rating, genre	Cultural discounting of imported U.S. movies results in stronger performance of domestic movies
Wu et al. (2022)	2009-2014	China	No	Delayed release	China selectively imports U.S. movies and often delays their release to protect local movies. Delayed release reduces box-office performance
This paper	*2012-2021*	*13 countries*	*Yes*	*Facial Similarity*	*Actors' facial similarity in a U.S. movie's cast reduces its box-office performance in ESEA countries. This effect is weakened as immigration, Internet penetration, and star power increase and strengthened as cast size increases.*

Table III: Variables and Measures

	Variable	Measure
Dependent Variable	Box-Office Performance	Total revenue in USD in the country, logged and winsorized at 2.5% and 97.5%*
Independent Variable	Facial Similarity	Average facial similarity of each pair of principal cast members starring in the movie, winsorized at 95%**
Moderating Variables	Immigration	Percentage of the country's population constituted by immigrants
	Internet Penetration	Percentage of the country's population that uses the Internet
	Cast Size	Number of principal cast members in the movie
	Star Power of Actors	Average movie gross in USD for each principal cast member, averaged across all principal cast members, prior to the movie's worldwide release date, logged and winsorized at 2.5% and 97.5%*
Control Variables	Budget	Production budget in USD, logged and winsorized at 2.5% and 97.5%*
	Director Power	Average movie gross in USD for the movie's director(s) prior to the movie's worldwide release date, logged and winsorized at 2.5% and 97.5%*
	Distribution Intensity	Number of theatrical engagements for the movie in the country (one theatrical engagement means being played in a theater for one week), divided by 10^3
	Competitive Intensity	Number of movies released in the year of a movie's initial release in the country
	Critic Review Score	Aggregated critic review score from rottentomatoes.com (0-100)
	Academy Award	1 if the movie won the Academy Award for Best Picture, 0 otherwise
	General Audience Unsuitability	1 if MPAA rating is PG-13 or Restricted (the tightest two ratings in the sample), 0 otherwise
	Sequel	1 if the movie is a sequel, 0 otherwise
	Remake	1 if the movie is a remake, 0 otherwise
	Spin-off	1 if the movie is a spin-off, 0 otherwise
	Previous Releases	Number of ESEA countries in which the movie has been released before release in the country
	Time-lag	Number of days between the worldwide release of the movie and release in the country
	Proportion of Asian Actors	Percentage of Asian principal cast members
	Proportion of Black Actors	Percentage of Black principal cast members
	Proportion of Hispanic Actors*	Percentage of Hispanic principal cast members
	Proportion of Female Actors	Percentage of female principal cast members
	Diversity	1 minus the sum of squared percentages of Asian, Black, Hispanic, and White principal cast members
	Major Studio	1 for movies produced or distributed (in the U.S.) by major studios (e.g., Warner Bros, 20th Century Fox, etc.), 0 otherwise

*The results do not change if we winsorize the variable at 1% and 99%.
**The results do not change if we winsorize the variable at 97.5% or 99%.

Table IV: Descriptives

Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. Box-Office Performance	13.44	2.01	**1.00**																							
2. Facial Similarity	8.98	12.92	**-0.08**	**1.00**																						
3. Immigration	12.02	17.08	**-0.16**	0.03	**1.00**																					
4. Internet Penetration	68.75	23.78	**0.14**	-0.03	**0.41**	**1.00**																				
5. Cast Size	3.15	2.49	0.03	**0.36**	0.01	-0.01	**1.00**																			
6. Star Power of Actors	17.25	4.48	**0.10**	**0.11**	0.00	0.00	**0.16**	**1.00**																		
7. Budget	17.41	1.09	**0.52**	**0.04**	**-0.10**	**-0.11**	**0.13**	**0.34**	**1.00**																	
8. Director Power	14.87	6.83	**0.16**	**0.05**	-0.04	-0.03	**0.10**	**0.20**	**0.31**	**1.00**																
9. Distribution Intensity	6.73	33.37	**0.37**	-0.03	**-0.14**	**-0.08**	**0.05**	0.03	**0.17**	**0.06**	**1.00**															
10. Competitive Intensity	44.41	24.78	0.03	0.00	**0.21**	**0.38**	0.00	**-0.04**	**-0.10**	-0.02	**-0.06**	**1.00**														
11. Critic Review Score	58.10	26.64	**0.04**	**0.07**	0.00	**0.08**	0.02	**0.10**	**-0.04**	**0.16**	0.02	**-0.04**	**1.00**													
12. Academy Award	0.01	0.11	-0.02	**0.09**	0.02	0.01	0.01	0.01	**-0.06**	0.04	0.00	0.01	**0.13**	**1.00**												
13. General Audience Unsuitability	0.93	0.26	0.00	0.03	0.00	-0.01	**0.08**	0.01	-0.03	0.01	-0.01	0.03	0.01	0.03	**1.00**											
14. Sequel	0.26	0.44	**0.27**	0.02	**-0.04**	**-0.06**	**0.11**	**0.05**	**0.30**	0.04	**0.07**	**-0.08**	**-0.08**	**-0.07**	**0.08**	**1.00**										
15. Remake	0.03	0.16	-0.02	**0.06**	-0.01	0.00	**0.04**	0.02	0.00	0.00	-0.01	0.03	**-0.10**	-0.02	0.03	**-0.10**	**1.00**									
16. Spin-off	0.01	0.10	**0.11**	**-0.05**	-0.01	0.00	-0.01	0.01	**0.09**	**-0.05**	0.03	**-0.05**	-0.02	-0.01	**-0.09**	**-0.06**	-0.02	**1.00**								
17. Previous Releases	2.43	2.62	**0.08**	0.01	**-0.11**	**-0.15**	0.01	**0.06**	**0.16**	**0.06**	0.02	**-0.21**	0.03	-0.01	-0.01	**0.13**	-0.01	0.03	**1.00**							
18. Time-lag	48.97	91.59	**-0.16**	0.01	**-0.10**	**0.19**	-0.03	**-0.05**	**-0.28**	**-0.08**	-0.01	**0.07**	**0.06**	**0.04**	**-0.04**	**-0.19**	0.00	0.00	**-0.17**	**1.00**						
19. Proportion of Asian Actors	0.02	0.10	**0.05**	**-0.06**	-0.02	0.02	**0.19**	**-0.06**	0.01	-0.01	0.02	-0.03	0.01	-0.03	**0.06**	0.00	0.00	-0.02	0.03	-0.03	**1.00**					
20. Proportion of Black Actors	0.10	0.22	**-0.04**	-0.04	0.00	**0.05**	**0.05**	-0.04	-0.04	-0.03	0.01	**-0.08**	-0.01	**0.10**	**0.06**	**0.09**	-0.02	-0.01	0.01	**0.04**	**-0.05**	**1.00**				
21. Proportion of Hispanic Actors	0.10	0.22	**0.10**	**-0.18**	0.00	-0.02	-0.02	**0.06**	**0.08**	**0.07**	0.04	-0.03	**-0.05**	**-0.05**	**-0.13**	**-0.08**	0.01	**0.05**	0.04	**-0.07**	-0.03	**-0.08**	**1.00**			
22. Proportion of Female Actors	0.37	0.34	**-0.09**	**-0.08**	0.01	**0.05**	-0.02	**-0.20**	**-0.28**	**-0.09**	-0.03	-0.01	**-0.07**	**-0.07**	0.00	0.03	0.00	**0.08**	-0.02	0.03	-0.01	**-0.08**	**-0.10**	**1.00**		
23. Diversity	0.17	0.23	**0.08**	**-0.14**	-0.01	0.01	**0.44**	**0.11**	**0.11**	0.01	**0.06**	**-0.04**	**-0.07**	-0.02	**0.10**	**0.07**	**0.04**	**0.08**	0.04	**-0.04**	**0.28**	**0.26**	**0.32**	**-0.08**	**1**	
24. Major Studio	0.89	0.31	**0.26**	0.02	-0.03	**-0.11**	0.00	**0.12**	**0.36**	**0.16**	**0.05**	**-0.18**	-0.01	**-0.08**	**-0.06**	**0.17**	0.01	0.03	**0.20**	**-0.28**	0.01	0.00	**0.06**	**-0.10**	0.028	**1**

Note: N = 2,616. Significant correlations ($p < 0.05$) in bold.

Table V: Box-Office Performance Model: Results

Dependent Variable:	Box-office Performance		
	Column 1	Column 2	Column 3
Facial Similarity (H_1)		-.004 (.002)**	-.03 (.01)***
Facial Similarity x Immigration (H_2)			.0002 (.0001)***
Facial Similarity x Internet Penetration (H_3)			.0001 (.0001)*
Facial Similarity x Cast Size (H_4)			-.003 (.001)**
Facial Similarity x Star Power (H_5)			.001 (.0004)***
Control Variables			
Immigration	-.11 (.04)**	-.11 (.04)**	-.12 (.04)**
Internet Penetration	.02 (.004)***	.02 (.004)***	.02 (.004)***
Cast Size	-.02 (.01)**	-.01 (.01)	.04 (.02)**
Star Power	-.01 (.004)*	-.01 (.004)*	-.01 (.004)***
Budget	.66 (.04)***	.65 (.04)***	.65 (.04)***
Director Power	-.004 (.002)	-.004 (.002)	-.004 (.002)
Distribution Intensity	.001 (.001)	.001 (.001)*	.001 (.001)*
Competitive Intensity	-.002 (.001)	-.002 (.001)	-.002 (.001)*
Critic Review Score	.01 (.002)***	.01 (.002)***	.01 (.002)***
Academy Award	.66 (.27)**	.69 (.27)**	.75 (.30)**
General Audience Unsuitability	-.06 (.06)	-.06 (.06)	-.05 (.06)
Sequel	.50 (.08)***	.50 (.08)***	.50 (.09)***
Remake	.12 (.13)	.14 (.12)	.12 (.12)
Spin-off	.95 (.25)***	.96 (.25)***	.97 (.24)***
Previous Releases	.02 (.01)**	.02 (.01)**	.02 (.01)*
Time-lag	-.003 (.001)***	-.003 (.001)***	-.003 (.001)***
Proportion of Asian Actors	.87 (.19)***	.82 (.19)***	.84 (.17)***
Proportion of Black Actors	-.19 (.13)	-.18 (.14)	-.15 (.14)
Proportion of Hispanic Actors	.30 (.09)***	.29 (.09)***	.33 (.09)***
Proportion of Female Actors	.20 (.07)**	.18 (.07)**	.16 (.06)**
Diversity	.08 (.10)	.004 (.09)	-.15 (.11)
Major Studio	.55 (.07)***	.55 (.06)***	.57 (.06)***
Genre Indicators	*YES*	*YES*	*YES*
Year Indicators	*YES*	*YES*	*YES*
Country Indicators	*YES*	*YES*	*YES*
Observations	*2,616*	*2,616*	*2,616*
R^2	*0.69*	*0.69*	*0.70*
AIC	*8,017.77*	*8,013.13*	*7,985.98*

Notes: Cluster-robust standard errors in parentheses; *p < .10. **p < .05. ***p < .01. The models include a constant. Indicators are included but not reported in the interest of brevity. The results are robust upon the exclusion of control variables and indicators.

Table VI: Box-Office Performance Model: Robustness Checks

	GC	Control Function	Heckman's Sample Selection	Highest Facial Similarity	No Asian Actors	No Movies with One Principal Cast Member	Dropping the First Two Years of Data
Dependent Variable:							
	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
Facial Similarity (H_1)	-.04 (.01)***	-.05 (.01)***	-.03 (.01)***	-.02 (.005)***	-.03 (.01)***	-.04 (.01)***	-.03 (.01)***
Facial Similarity x Immigration (H_2)	.0002 (.0001)***	.0002 (.0001)***	.0002 (.0001)***	.0001 (.00003)***	.0002 (.0001)***	.0002 (.0001)***	.0002 (.0001)**
Facial Similarity x Internet Penetration (H_3)	.0001 (.0001)*	.0002 (.0001)*	.0001 (.0001)	.0001 (.00002)**	.0001 (.0001)*	.0001 (.0001)**	.0002 (.0001)*
Facial Similarity x Cast Size (H_4)	-.003 (.001)**	-.003 (.001)**	-.003 (.001)*	-.002 (.001)*	-.003 (.002)	-.003 (.001)*	-.003 (.001)***
Facial Similarity x Star Power (H_5)	.001 (.0004)***	.001 (.0004)***	.001 (.0004)***	.001 (.0002)***	.001 (.0004)***	.002 (.001)**	.001 (.0004)***
GC	.04 (.03)						
Control Function		.02 (.005)***					
IMR			-.49 (.17)**				
Observations	*2,616*	*2,616*	*2,616*	*2,616*	*2,411*	*1,841*	*2,275*
R^2	*0.70*	*0.70*	*0.71*	*0.70*	*0.70*	*0.70*	*0.70*

Notes: Cluster-robust standard errors in parentheses; *p < .10. **p < .05. ***p < .01. The models include a constant. Indicators and controls are included but not reported in the interest of brevity.

Table A: Celebrity Lookalikes and Facial Similarity

Actor 1	Actor 2	Score
Jeff Bridges	Kurt Russell	56.57
Mila Kunis	Sarah Hyland	59.95
Margot Robbie	Samara Weaving	65.28
Nina Dobrev	Victoria Justice	66.90
Logan Marshall-Green	Tom Hardy	67.43
Bryce Dallas Howard	Jessica Chastain	68.22
Henry Cavill	Matt Bomer	69.56
Amy Adams	Isla Fisher	72.00
Haley Lu Richardson	Zoey Deutch	74.36
Gabrielle Union	Regina Hall	82.24
Rachael Leigh Cook	Winona Ryder	82.36