Intellectual Property Piracy and the Intersectionality of Artistic Merit, Gender, and Race

Anirban Mukherjee,[1*] Hannah H. Chang[2]

[1]Samuel Curtis Johnson Graduate School of Management, Cornell University, Sage Hall, Ithaca, NY 14850, USA

[2]Lee Kong Chian School of Business, Singapore Management University, 50 Stamford Road, Singapore, 178899

*To whom correspondence should be addressed; E-mail: am253@cornell.edu.

Abstract

We pivot from traditional theories of intellectual property piracy that focus on financial drivers—such as pricing, accessibility, and affordability—to investigate the intersectionality of artistic merit, gender, and race. Utilizing an 18-year dataset, we examine the illicit release (leaking) of films at the Academy of Motion Picture Arts and Sciences, the organization responsible for the Oscars. Despite stringent safeguards, 54% of films, amounting to $41 billion in production expenditures and $66 billion in U.S. box-office revenues, were leaked between 2003 and 2020. Employed interlocked hypotheses and falsification tests, we show the leak of films aligned with increased access to high-quality content featuring historically marginalized gender groups. We do not observe similar findings for historically marginalized racial groups. Films recognized for artistic excellence and those featuring white female Oscar nominees were more likely to be leaked. The impact of white female nominees exceeded that of white male nominees; both groups exceeded that of non-white nominees. We contrast such findings with leaks in for-profit channels where patterns align with traditional financial factors but not the intersectionality of artistic merit, gender, and race. Our findings invite a reassessment of intellectual property management strategies, advocating for a more balanced approach incorporating factors such as fairness and cultural inclusivity.

Keywords: Gender, Race, Diversity, Equity, Inclusion.

Introduction

"The academy, like our industry, should reflect the world in which we live," said David Heyman, a producer of "Barbie." "The fact that it doesn't is just wrong."

—'Barbie' Ruled the Box Office, but 2023 Was Tough for Women in Hollywood, *NYTimes*, March 5, 2024.

Issues of representation and diversity have long been topics of discussion in women's studies, media and culture economics, and popular media (Marshment 1997; Smith 1997), predating the MeToo movement but gaining renewed urgency from it (Luo and Zhang 2022). Despite some evidence of progress, challenges persist. As of the latest data, only 34% of the members of the Academy of Motion Picture Arts and Sciences (hereafter referred to as the Academy) are women, and 18% are persons of color (Sperling 2024). This marks an improvement from 2015, when only 25% were women and 10% were people of color, following the Academy's A2020 initiative aimed at enhancing representation. A detailed examination of film data reveals similar trends, with 30% of the top 100 films of 2023 featuring a female-identified actor in a lead or co-lead role, up from 20% in 2007. Moreover, in 2023, only 3 movies led or co-led by women featured actresses aged 45 or older at the time of theatrical release, compared to 32 films that featured men in the same age bracket (Neff, Pieper, and Smith 2024).

Against this backdrop of persistent inequity and inequality, we provide evidence consistent with the notion that artistic merit, gender, and race are determinants of intellectual property piracy [1]. Here, we deviate from the traditional conceptualization of piracy as a form of white-collar crime—a financially motivated illegal act (Liebowitz 2006). Such characterizations are typical as consumers balance accessibility, affordability, and ethical considerations (Chae, Ha, and Schweidel 2023; Chen, Hu, and Smith 2019; Ma et al. 2014; Sivan, Smith, and Telang 2019). Prior studies explore the interplay between legal and illegal consumption (Danaher and Smith 2014; Ho et al. 2018; Oberholzer-Gee and Strumpf 2007), the influence of market forces on piracy dynamics (Peitz and

[1] 'Piracy' refers solely to intellectual property piracy.

Waelbroeck 2006), and the role of enforcement (or its absence) in combating piracy (Landes and Lichtman 2003; Reimers 2016).

Our evidence relates to a highly visible and impactful example of piracy: the unauthorized release, or 'leak,' of pre-release 'screeners' given to members of the Academy. The Academy, responsible for presenting the Oscars, comprises the most eminent figures in the film industry—top directors, actors, writers, etc. The Oscars are nominated and selected through voting. To facilitate informed choices, Academy members are entrusted with screeners—home video versions of films under consideration—that are licensed solely for the members' viewing. Screeners are protected with stringent digital rights management protocols and legal agreements to prevent unauthorized distribution. Yet, despite these safeguards, 54% of films nominated over the 18-year period covered by our data (2003 to 2020) had their Oscar screeners leaked. A leak occurs when a digital copy of a film (in this case, the Oscar screener) is uploaded to a file-sharing platform or other unauthorized channels. A single leak can lead to billions of dollars in losses as the uploaded file can be replicated and distributed indefinitely. Thus, 54% of films being leaked corresponds to billions of dollars in lost revenue and profitability.

Several factors challenge classical explanations. First, piracy poses a substantial threat to the profitability of the entertainment industry. For instance, the Motion Picture Association of America estimates the annual financial loss due to piracy at $58 billion, and TorrentFreak reports that one in three Internet users engages in online pirated media consumption. While precise estimates of the damages caused by Oscar screener leaks are difficult to ascertain, a proxy for the impact can be gauged by the fact that the films affected by these leaks had a cumulative production budget exceeding $41 billion and generated over $66 billion in domestic U.S. box-office revenues. Consequently, Academy members implicated in screener leaks face stringent penalties, including financial restitution lawsuits and expulsion from the Academy. They risk professional repercussions, such as potential blacklisting, given that their actions critically undermine the revenue foundations of movie studios and publishers.

Second, Academy members stand to lose financially from piracy. Membership in the Academy is secured through outstanding contributions to the field, such as winning an Oscar. Hence, members of the Academy are the industry elites whose financial compensation, and that of their peers, includes ‘residuals,’ which are a share of the post-theatrical (legal) revenues. Piracy reduces residuals by enabling free, illegal post-theatrical access to films.

Third, members of the Academy are well-positioned to ensure the safety of Oscar screeners should they choose to do so. While specific numbers are hard to obtain, Hollywood insiders, such as Academy members, are known to spend vast amounts on personal security. Given their financial resources and access to top-of-the-line security measures, Academy members have the means to safeguard their Oscar screeners from unauthorized access or distribution if keeping them secure is their top priority.

Over 18 years, more than half of the Oscar film screeners were leaked—the persistence of piracy, and the extent of financial damages associated with it, indicate that the leaks were not random occurrences or isolated acts of negligence. Instead, the leaks suggest systemic factors such that even in the face of immense consequences for both the individuals tasked with safeguarding the copies and the industry at large, piracy persisted. In response, we propose an impetus to redress imbalances in cultural capital and enhance underrepresented voices within the industry (Ostrom 1990; Turner et al. 1987; Yar 2005). Thus, we reframe intellectual property piracy within a more nuanced ethical framework, fundamentally reassessing foundational assumptions and introducing oft-neglected dimensions of fairness, justice, and morality into the discourse (Randazza 2015).

These elements form our contributions to an emerging dialogue on issues of diversity, equity, and inclusion (Kim, Jiang, and Thomadsen 2023; Thomas, Taylor, and Chintagunta 2023). Central to this discussion are concepts of fairness and justice, which have been examined in diverse domains such as pricing strategies (Moshary, Tuchman, and Vajravelu 2023), financial access (Ozturk, He, and Chintagunta 2022), policing (Ananthakrishnan, Hasan, and Kumar 2022), and media representation (Goli and Mummalaneni 2023). While existing literature often highlights disadvantages faced by women—such as ‘pink taxes,’ higher interest rates, or limited career opportunities—our study introduces the notion of protest subverting existing institutional controls, even at the risk of jeopardizing personal careers and individual prospects. Our findings illustrate a complex duality: there is strong institutional support for disseminating content associated with successful white women, yet this support contrasts sharply with the statistically nonsignificant effect observed for non-white women. This intersectionality suggests systematic and persistent effects of gender and race that may extend beyond universal motives to notions of group affiliation and similarity that underpin Herbert Simon's notion of selective altruism (Simon 1990).

Data and Empirics We develop a dataset tracking 18 years of Oscar screener leaks, integrating it with key descriptors of Oscar nominees, award nominations, and various metrics of commercial success. The data also includes two other forms of leaks: cam and telesync leaks. Unlike screener leaks, which originate from pre-release home video copies on formats like DVD or Blu-ray, cam and telesync leaks originate from illicit in-theater recordings requiring more organizational resources and are typically executed by profit-motivated piracy groups. For instance, a telesync leak requires privileged access to the projection booth in a movie theater and a direct connection to the sound source, such as an FM microbroadcast provided for the hearing-impaired. This form of recording cannot be undertaken without the direct complicity of the projection booth operator and is typically conducted by organized criminal for-profit piracy groups.

The data enable the specification of a series of interlocked hypotheses and falsification tests to pinpoint empirical generalizations. Specifically, if theorizing on fairness and justice holds, we may expect to see an effect of artistic merit on screener leaks (hypothesis test) but not on cam and telesync leaks (falsification tests). Furthermore, we would expect to see an effect of commercial appeal on cam and telesync leaks (hypothesis tests) but not on screener leaks (falsification test). The intersection of these interlocked tests provides a means to gather evidence.

Additionally, we capture data on the gender and race of Oscar nominees to incorporate group membership, discerning if the Academy's concerns are selective—if they apply universally or selectively to members of specific gender and racial groups (Epstein 1993; Wynn et al. 2018). We conduct an additional set of interlocked falsification tests where our theorizing suggests we should observe a nuanced interplay of artistic merit, as evaluated through the lens of Oscar nominations, intersecting with gender and race in the occurrence of screener leaks, but not in cam and telesync leaks.

Synopsis of Findings We uncover a systematic and predictable relationship between artistic merit, as gauged by criteria like festival awards, and the probability of a film's Oscar screener being leaked. This contrasts with cam and telesync leaks, where commercial appeal, measured through variables such as box office earnings, is the primary empirical predictor. Measures of commercial appeal are not found to be implicated in screener leaks. This is consistent with screener leaks being driven by artistic merit, while cam and telesync leaks are driven by commercial appeal.

Films with more white[2] female Oscar nominees are more susceptible to screener leaks. The influence exerted by white female nominees surpasses that of their male counterparts, and both significantly overshadow the incidence of leaks associated with non-white nominees, irrespective of gender. These patterns align with the motivation of Oscar screener leakers to disseminate films to broaden access to artistically significant works, particularly for films that star or otherwise feature members of certain historically marginalized genders[3]. However, this inclination does not appear to extend to non-white contributors, raising critical questions about the representational dynamics within the industry.

These findings advocate for a nuanced reevaluation of strategies. While the primary objective of content availability and pricing strategies (e.g., streaming, paywalls) may be profit maximization, the evidence suggests that there is merit in pursuing a more equitable distribution of cultural capital.

[2]Gender and race classification are based on the names provided during the Oscars, utilizing a wealth of historical, self-reported data, as detailed in our methods section. Regrettably, owing to the limitations of data and methodology, our classification schema lacks the granularity to include non-binary genders and a more nuanced description of racial identities. This decision to employ a binary classification system is guided by sample size considerations and data limitations, and does not signify a normative stance on gender or race. It is crucial to underscore that these constraints do not diminish the importance of a more inclusive and intersectional understanding of race and gender, an aspect of societal representation that this study aims to respect and uphold.

[3]The term 'historically marginalized' reflects long-standing social and institutional biases that these groups face. It recognizes both the statistical underrepresentation in the film industry and the systemic challenges contributing to their limited visibility and inclusion. Although the term aims for greater inclusivity, it should be noted that its scope is limited by data and model constraints and does not capture the full spectrum of marginalization stemming from intersectional identities and experiences.

This calls for a critical examination and possible reconfiguration of existing mechanisms that, while effective in safeguarding profitability, may inadvertently impede broader availability and thus be counterproductive in the broader socio-economic context (Boldrin, Levine, et al. 2008). These insights hold far-reaching implications for practice and research in the political economy of intellectual property rights (Giblin 2013; Litman 1996; Weinberg et al. 2021). In a milieu where industries like software, media, and luxury goods rely heavily on the protection of intellectual assets (Posner 2005; Towse 2006), they invite a reassessment of regulatory paradigms and market-driven tactics that often prioritize profitability (Ginsburg 2001).

Roadmap. Our paper is structured as follows: Next, we present a conceptual framework that relates piracy to non-financial determinants. We then outline our empirical strategy. As the institutional context may be new to many readers, the subsequent section provides crucial details needed to follow the study. The next section outlines the data. Then, we present our results. The last section discusses the implications of the findings and suggests potential avenues for future research.

Literature Review

We argue that piracy is driven by a complex interplay of ethical considerations, grounded in contexts characterized by risk and moral ambiguity (Kahneman 2011; Tversky and Kahneman 1992). For instance, piracy may serve as a means to address perceived imbalances within the film industry, especially regarding the commercialization of cinema. This viewpoint aligns with seminal theories on social equity and fairness, suggesting that individuals are inclined to violate legal norms contributing to systemic injustices (Fehr and Schmidt 1999; Güth, Schmittberger, and Schwarze 1982; Henrich et al. 2001; Konow 2003; Trivers 1971). Furthermore, piracy may be envisioned as a redistributive mechanism for cultural capital—a concept deeply entrenched in sociology (Bourdieu 1987; Erickson 1996; Lizardo 2006).

These arguments find support in prior empirical evidence indicating a disjunction between commercial success and artistic value. Research has shown that industry insiders often advocate for less-publicized, independent films, in contrast to widespread acclaim typically resulting from aggressive marketing campaigns (Holbrook 1999; Holbrook and Addis 2007; Peterson and Kern 1996; Simonton 2011; Spiller and Belogolova 2017). The dichotomy between commerce and artistry brings ethical considerations into focus. They suggest that acts of piracy might, from the perspective of those committing these acts, be viewed as deliberate responses to what is perceived as overly restrictive intellectual property regimes (Boldrin and Levine 2002; Karaganis 2011; Lessig 2004; Oberholzer-Gee and Strumpf 2007). Despite the considerable legal and reputational risks involved, leakers may be guided by an ethical framework that prioritizes artistic integrity and diversity (Ostrom 1990; Turner et al. 1987; Yar 2005).

Moreover, their concerns may be preferentially directed toward films whose artists share their identities. Theory posits that shared identity, reciprocal obligations, and moral beliefs significantly affect the inclination to assist groups or individuals (Fehr and Fischbacher 2003; Fong, Bowles, and Gintis 2006). Empirical studies support this view, indicating that factors like ethnicity, gender, and social proximity can shape altruistic actions (Tajfel et al. 1971; Whitt and Wilson 2007). Consequently, the advocacy for diversity and inclusion among Academy members may exhibit selectivity across marginalized groups, thereby raising questions concerning the equitable allocation of their efforts (Collins 2022; Erigha 2019). An emphasis on identity and social closeness, particularly through the lenses of gender and race, highlights deep-rooted issues of selectivity and discrimination within the Academy.

Media Piracy Our research makes three further contributions to the literature. First, existing research on media piracy has primarily focused on readily accessible demographic groups, such as college students (Limayem, Khalifa, and Chin 2004; Waldfogel 2010) and contributors to online forums (Steinmetz and Tunnell 2013). We broaden the evidentiary base to include a more established and influential demographic: members of the Academy. This exclusive cohort comprises globally recognized industry professionals and celebrities who possess both the financial resources and the cultural capital to leak films based on moral convictions. However, they also face distinct risks in engaging in piracy, such as severe reputational damage, financial penalties, and legal repercussions—risks that are notably different from those faced by previously examined populations (Dejean 2009). The inclusion of this demographic provides unique insights into the complex interplay of financial, ethical, and reputational considerations in the decision-making process surrounding film piracy.

Second, our study serves as a pioneering investigation into the non-financial determinants of piracy, thereby addressing a gap in the literature (Belleflamme, Peitz, et al. 2014; Smith and Telang 2012). Specifically, extant papers have centered on the economic determinants of authorized and unauthorized media consumption (Hong 2013; Reimers 2016; Sundararajan 2004). This focus is confirmed by a review of 257 articles on media piracy (Lowry, Zhang, and Wu 2017), in which non-financial motivations are relegated to the periphery and are primarily examined via ethnographic and qualitative approaches (e.g., Condry 2013). In stark contrast, our research utilizes an extensive 18-year empirical dataset, enabling us to rigorously test the linkage between piracy and non-financial motivations. This methodological shift not only broadens the scope of inquiry but also brings quantitative rigor to an area traditionally explored through qualitative means.

Third, our research is among the first to investigate the initial catalysts behind a film leak, defined as the film's first unauthorized release in a specific format. Unlike extant studies, which have predominantly scrutinized the determinants and psychology of individuals engaging in post-leak piracy—typically consumers and file-sharers (Danaher et al. 2014; Sivan, Smith, and Telang 2019; Zentner 2006)—we pivot the analytical lens toward the originators of these leaks. This conceptual shift critically reframes the research question, enabling us to probe the psychology of individuals who, despite possessing privileged access to content and being fully aware of potential legal and reputational repercussions, choose to breach the trust vested in them. Importantly, unlike consumer-driven piracy, the instigators of these leaks are characterized by both trust and privileged access—attributes conspicuously absent in other piracy contexts.

Empirical Strategy

Our empirical approach is grounded in the methodology of interlocked falsification and hypothesis testing. Falsification testing involves disproving rather than proving hypotheses. Interlocked falsification and hypothesis testing involve concurrently examining multiple hypotheses across different datasets, with each hypothesis expected to hold true in one dataset but not in others. The strength of interlocked testing lies in its ability to leverage the expected inconsistencies across datasets to bolster the credibility of a hypothesis.

Specifically, our research concurrently examines multiple hypotheses across four types of leaks: screener, cam, telesync, and other.

- Screener leaks are unauthorized leaks of home video copies of films provided to Academy members for Oscar voting purposes.
- Cam leaks are secret recordings of films made in a theater using a compact digital camcorder.
- Telesync leaks are of higher quality, usually involving a professional camera on a tripod in the projection booth. The audio is often captured via a direct connection to the sound system or by positioning wireless microphones near the speakers.
- Other leaks can originate from sources like Telecine, R5, Pay-Per-View, Webrip, and HDRip.

We posit that the influence of artistic merit on screener leaks, which originate from Academy members, aligns with our conceptual framework. This framework positions piracy as an ethically grounded action to counter systemic injustices and redistribute cultural capital (Bourdieu 1987; Fehr and Schmidt 1999; Güth, Schmittberger, and Schwarze 1982). Hence, we expect to find a significant and positive relationship between a film's artistic merit and its likelihood of being subject to a screener leak. In contrast, variables known to predict commercial appeal, such as production budget and box office earnings, are anticipated to be nonsignificant if the piracy actions of Academy members are not profit-driven.

Conversely, cam and telesync leaks are usually carried out by profit-seeking pirate groups that often target commercially successful films. These groups generate revenue through advertising, subscriptions, donations, and selling pirated material (Choi and Perez 2007; Elberse 2010; Liebowitz 2006; Smith and Telang 2012). Therefore, we hypothesize that for these groups, commercial appeal is the primary driver. Hence, we expect factors such as box office gross to be the predominant predictors. Additionally, given the prior empirical evidence suggesting a disjunction between commercial success and artistic value (Holbrook and Addis 2007; Spiller and Belogolova 2017), the relationship between artistic merit and subsequent channel revenues is unclear. Thus, we expect measures of artistic merit to be nonsignificant.

Leaks from other sources, such as Telecine, R5, Pay-Per-View, Webrip, and HDRip, are opportunistic and unpredictable in nature. Consequently, we do not anticipate a consistent relationship with either commercial appeal or artistic merit for these types of leaks. The varied origins of these leaks make it challenging to establish clear patterns or motivations, as they stem from diverse piracy activities beyond the ethical or commercial motivations of screener, cam, and telesync leaks.

We incorporate the count of Oscar nominees to examine whether the motivations behind screener leaks selectively target specific demographic groups. This analysis seeks to ascertain whether the Academy's concerns about diversity and representation notably influence the likelihood of screener leaks. Given that screener leaks uniquely originate from Academy members, we hypothesize that these leaks will reflect the Academy's fairness concerns, manifesting in the significance of the count of Oscar nominees—a measure of artistic merit—specifically in the context of screener leaks.

We also incorporate the gender and race profiles of Oscar nominees to test whether the motives behind screener leaks manifest selectively, preferentially targeting films with more nominations for historically underrepresented groups. Given theories on shared identity and empirical evidence of in-group favoritism (Fehr and Fischbacher 2003; Fong, Bowles, and Gintis 2006; Tajfel et al. 1971; Whitt and Wilson 2007), the Academy's aims for diversity and fairness may be selective across marginalized groups. Consequently, films with higher counts of Oscar nominations for white women or racial/ethnic minorities may face greater odds of a screener leak by Academy members seeking to promote these groups' artistic merit, as nominations signify peer acknowledgment of excellence. However, cam, telesync, and other leaks, disconnected from the Academy's internal dynamics, will not demonstrate this pattern.

In sum, we seek to provide evidence that: (1) artistic merit influences screener leaks, which is consistent with the primary proposition; (2) artistic merit does not influence cam, telesync, and other leaks, thereby establishing the disjunction between artistic merit and commercial appeal (see Table 6 in Luan and Sudhir 2010 for additional empirical evidence); (3) commercial appeal does not influence screener leaks, which is consistent with the fact that Academy members are vastly successful and unlikely to be lured by the relatively meager compensation from for-profit piracy; (4) commercial appeal influences cam and telesync leaks, which are mainly conducted by for-profit pirate groups; and (5) document any selectivity in Academy members' concerns which may manifest in films with contributors from different historically marginalized racial and gender groups being differentially likely to be leaked.

Temporal precedence plays a crucial role. As detailed in the following section, our independent variables are established before the Oscars voting period and, consequently, prior to the distribution of Oscar screeners. This sequence ensures these variables remain uninfluenced by Oscar screener piracy. Specifically, the production budget is set during the pre-production phase, well before a film's theatrical release. Box office earnings, a vital indicator of commercial success, are accumulated in accordance with the Oscars' eligibility rules, which require films to be screened in the calendar year preceding the awards year (McKenzie 2023). Furthermore, the Oscars season is often a slower period for cinemas (Einav 2007). As the Oscars mark the end of the awards season, award nominations are firmly established and known to Academy members by the time of Oscar screener distribution and any potential leaks. These industry norms and timelines significantly constrain the range of possible influences and aid in identification.

Institutional Context

The Academy, a prestigious Hollywood institution, was established in 1927. It consists of approximately 10,000 voting members who work in diverse sectors of the film industry, including acting, directing, writing, and sound editing. To be eligible for Academy membership, individuals must have substantial work experience and make significant contributions to the film industry. Oscar nominees are often automatically considered for membership, while other candidates must be endorsed by two current members of their desired branch. Each branch has specific requirements for membership, such as minimum credits or recent work history in the respective field. This ensures that Academy members are accomplished professionals at the pinnacle of the film industry.

The Awards Season.—The awards season is an orchestrated sequence of film festivals, critics' awards, and industry guild events that culminates with the Academy Awards (Oscars). It commences with prestigious international film festivals like Cannes, Venice, Telluride, Toronto, New York, and AFI. These festivals provide a platform for films to gain early critical acclaim and momentum during the awards season. This is followed by critics' group awards like the New York Film Critics Circle and industry guild awards such as the British Independent Film Awards and the Hollywood Music in Media Awards. The Oscars are strategically positioned at the end of this sequence, with the outcomes of preceding awards shaping the narratives and expectations. Thus, they represent the pinnacle of a broader narrative constructed on the judgments of critics, guilds, and film organizations, celebrating the highest achievements in the film industry.

Oscar Nomination and Voting.—Academy Members both nominate and select the winners. During nomination, members receive a ballot listing films that meet specified qualification criteria. To be eligible, a film must be feature-length (over 40 minutes) and must have been publicly screened for paid admission for at least one week at a commercial theater in Los Angeles County during the previous calendar year. Members may nominate within their respective branches, with the exception of the 'Best Picture' category, which is open for nomination by all members. Nominees are announced in January. At selection, even though active and lifetime Academy members can vote in any category, the Academy discourages them from casting votes in categories outside their field of expertise. The results remain confidential until they are revealed at the Academy Awards ceremony, typically held in the first quarter of the year.

The Academy earnestly safeguards the integrity of Oscar voting. To minimize studio influence over its approximately 10,000 voting members, it imposes stringent regulations. These include limitations on filmmaker Q&A sessions, prohibitions on direct promotional campaigns targeting Academy members, and bans against accepting gifts from studios or their representatives. Advertising guidelines also deter studios from explicitly targeting Academy members. These rules aim to foster an environment conducive to impartial film evaluation, ensuring that decisions are based strictly on artistic quality, devoid of external influence.

Oscar Screeners.—To aid Academy members in making informed voting decisions, studios distribute 'screeners'—copies of films in home video formats such as DVD and Blu-Ray. Screeners often contain a watermark with the voter's name and address to deter unauthorized sharing or distribution. Along with the screener, the film's studio or distributor typically includes a letter stating the terms of use and explicitly warning voters against copying, distributing, or selling the screener.

Data

Collecting reliable data on digital piracy poses inherent challenges due to its clandestine nature. While past studies often relied on web scraping, this method has significant limitations when applied to the opaque piracy landscape. Pirate websites lack consistent standards for data structure and accessibility compared to legal platforms, resulting in potentially incomplete datasets. The shifting nature of these sites—frequent content changes, domain shifts, or sudden closures—further complicates data collection. Additionally, some pirates use advanced evasion techniques like encryption and peer-to-peer sharing, making their activities virtually undetectable to web scrapers. Consequently, previous piracy research has taken ethnographic approaches (Condry 2004), analyzed survey data or lab experiments using available samples like college students (Sinha and Mandel 2008), or studied natural experiments such as the 2012 Megaupload shutdown (Danaher and Smith 2014; Peukert, Claussen, and Kretschmer 2017). However, the idiosyncrasies of these methodologies raise questions about the generalizability of findings.

In contrast, our research employs a distinctive 18-year dataset from 2003-2020, capturing diverse piracy activities. It encompasses all full-length English feature films nominated for Oscars across categories like music, makeup, and costume design. The leak dates were collected by Andy Baio[4] using Pre-Database (PreDB) systems—specialized platforms for tracking pirated content in real-time without hosting it. PreDBs operate by 'spidering' top piracy sites and logging pre-release announcements from Internet Relay Chat channels used for real-time communication. Besides identifying new leaks, PreDBs also flag duplicates, counterfeits, and 'nuked' releases—defective or rule-violating copies in pirate parlance. The data chronicles when each film first became available on various pirate channels, filtering out any nuked copies. Importantly, it reflects information accessible to consumers seeking to pirate these films.

In the early years of the data, leak dates were sourced primarily from VCD Quality and Nforce, digital media news sites known for regularly updating pirated content releases. Their credibility within the online piracy community establishes them as reliable sources for accurate leak dates. As the data progressed into more recent years, ORLYDB and D00per became the sources for leaks in 2015 and 2016, respectively. Like VCD Quality and Nforce, these platforms track pirated content releases in real-time across media types like music, films, TV, and software. Starting in 2017, RLSBB.com became the primary leak date source, occasionally supplemented by PreDB.me (formerly D00per and Layer13.net). The consistent use of specialized piracy tracking platforms as data sources ensures the credibility of the leak dates over the 18-year span.

We examined 578 films nominated across the 2003 to 2020 awards seasons. In 2021, the Academy transitioned from physical screeners to a dedicated streaming app, motivated by environmental and pandemic-related concerns. While the 2020 season saw minimal disruptions, the 2021 and 2022 seasons experienced significant upheaval due to the pandemic. Given the myriad factors affecting screener piracy during these latter periods, our study is confined to pre-pandemic seasons prior to the shift away from physical screeners. This provides 18 consistent years of data from 2003-2020 for analysis.

[4]The authors express their gratitude for making this portion of the data available under a CC Attribution-NonCommercial-ShareAlike 3.0 license.

If piracy is fundamentally driven by demand for illicit content, then the best proxy for unrealized illicit demand is realized demand in the prior legal channel (the box office) and the marketing and production costs expended by the studio to drive demand. Accordingly, we augmented the dataset with U.S. box office gross and production budgets from IMDb and The Numbers. These variables indicate each film's commercial appeal and profitability. When figures were available from both sources, we averaged them. For missing data from one source, we used the available figure. When data were unavailable in both databases, we relied on credible online estimates. This comprehensive data provides proxies for the commercial appeal of each film.

Our measure of artistic excellence is based on a comprehensive dataset that we systematically compiled, detailing each film's award nominations across many major film awards, including the Academy Awards, the BAFTA Awards, the Screen Actors Guild Awards, and the Golden Globes Awards (Ginsburgh 2003). For example, '12 Years a Slave' accumulated 579 nominations across 120 different awards, including 9 Academy Award nominations, 10 BAFTA nominations, 4 Screen Actors Guild Award nominations, and 6 Golden Globes Award nominations. Although we recorded award wins, we excluded this variable from our main model due to its high correlation of 0.92 with nominations. In robustness checks, we verified that substituting nominations with wins yielded congruent results. The meticulous collection of nomination data provides a proxy for artistic excellence.

To address variations in studios' anti-piracy measures, we identified the production studio for each of the 578 films, comprising 66 unique studios. To preserve statistical power and avoid overfitting, we incorporated fixed effects for 16 studios that produced 10 or more Oscar-nominated films each. We conducted two robustness checks: one excluding all studio fixed effects, and another incorporating the full set of 66 studio fixed effects. These tests validate the robustness of our findings against alternative specifications for studio-specific anti-piracy strategies. The studio fixed effects help account for differences in anti-piracy efforts.

We introduced four auxiliary variables to control for demographic heterogeneity among the nominees, structured similarly to our awards nomination variable. These quantify counts of white female, white male, non-white female, and non-white male nominees. To operationalize these classifications, we aggregated all nominee names and applied a tiered, algorithmic gender analysis. Initially, we utilized the U.S. Social Security Administration's baby name database for gender assignment. When this data was insufficient, we consulted the U.S. Census data from the Integrated Public Use Microdata Series. In rare instances, we resorted to historical census microdata spanning 1801–1910 for six nations, as furnished by the North Atlantic Population Project (Mullen, Blevins, and Schmidt 2015). These procedures assigned gender probabilities based on the names as officially presented during the respective award ceremonies. Unidentifiable names were apportioned equally across both gender groups.

Subsequently, we employed a race classification algorithm analogous to our gender categorization technique to estimate the likelihood of a nominee being classified as 'white.' This algorithm aligns with the definitions set forth by the U.S. Office of Management and Budget, as evidenced in the 2000 and 2010 U.S. Census data files on race and ethnicity (Tzioumis 2018). Since we only had probabilistic data on each nominee's race and gender, we computed expected values of these variables by aggregating probabilities across all nominees for each film. This approach yielded a film-level variable that we could associate with instances of piracy.

We re-emphasize, for clarity, that our reliance on binary classifications for both gender and race is necessitated by the constraints of our research question and the limitations inherent in our dataset and methodologies. Despite the longitudinal extensiveness of our dataset—surpassing those in previous intellectual property piracy studies—it lacks the granularity required for a more nuanced categorization. Such fine-grained classification would likely result in the underrepresentation of certain categories, thereby introducing model estimation and data analysis complexities. Moreover, our classification algorithms draw from extensive self-reported datasets, such as the Census, which historically lack expansive response options. Therefore, while not ideal, the binary schema represents a practical compromise between analytic precision and data availability. We acknowledge these constraints and emphasize that our classifications cannot fully encapsulate real-world diversity.

Table 1 presents summary statistics for our dataset of 578 films, with leaks encoded as 1 and their absence as 0. In our dataset, 53% of films experienced screener leaks, 40% had cam leaks, 33% faced telesync leaks, and 37% encountered other leaks. The films averaged about 114 global nominations, highlighting their significance and caliber. All monetary figures are adjusted to 2020 U.S. dollars using the Consumer Price Index. On average, each film had a production budget of $71 million and accrued $115 million in U.S. box office revenue. Collectively, the films represent over $41 billion in production costs and generated more than $66 billion in box office revenue. These figures underscore the substantial economic implications of piracy.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
Leaks						
Screener	578	.53	.50	0	1	1
Cam	578	.40	.49	0	0	1
Telesync	578	.33	.47	0	0	1
Other	578	.37	.48	0	0	1
Award Nominations	578	113.91	102.50	1	80.50	579
Award Wins	578	37.19	43.38	0	22	307
Box Office	578	115.02	147.97	0	55.66	1,010.03
Production Budget	578	70.64	76.19	0	37.87	392.77
Oscar Nominees						
Female	578	.89	.99	0	.51	7.34
Male	578	2.03	2.06	0	1.00	9.97
White	578	2.15	2	0	1.35	10.39
Non-white	578	.77	.86	0	.50	6.05
White Female	578	.61	.72	0	.26	4.46
White Male	578	1.53	1.62	0	.94	7.82
Non-white Female	578	.28	.34	0	.25	2.89
Non-white Male	578	.49	.61	0	.27	4.28
Total	578	2.92	2.65	1	2	14

Note: The categories 'Screener,' 'Cam,' 'Telesync,' and 'Other' identify types of film leaks and are coded as binary variables (1 for presence, 0 for absence). Financial figures are in millions of 2020 U.S. dollars. Gender and race classifications are based on names self-identified by nominees at the Oscars and widely accepted dictionaries for race and gender assignment. These yield probabilistic data; expected values for race and gender counts were computed by aggregating probabilities across nominees for each film. The study does not intend to define or enforce binary gender categories. Limitations exist due to the probabilistic nature of our demographic classifications and reliance on self-reported, potentially fluid, identity markers.

The ratio of male to female nominees in our dataset is approximately 2.5:1, while the ratio of white to non-white nominees is close to 3:1. These proportions are relatively stable across categories; for instance, the ratio of white male to white female nominees aligns with the overall male-to-female ratio at about 2.5:1. As Figure 1 shows, the representation of gender/racial groups remained approximately constant over the 18-year span, underscoring the enduring underrepresentation of female and non-white nominees at the Oscars.

Results

We first investigate the relationship between the number of award nominations garnered by a film and the incidence of its screener being leaked. Our aim is to discern whether screener leaks display patterns that are distinct from other forms of piracy. Subsequently, we examine how these leaks are influenced by Oscar nominations, focusing on the mediating effects of gender- and race-related variables.

Model-Free Evidence: Artistic Excellence

Figure 2 presents box plots comparing our four principal independent variables—the counts of award nominations and wins, box office revenue, and production budget—across films with leaked and unleaked screeners. Significant disparities are evident in the counts of award nominations and wins between these two categories. The absence of overlapping confidence intervals for the median values of these metrics strongly indicates a statistically significant link between a film's artistic excellence, as measured through award nominations and wins, and its susceptibility to piracy. Conversely, the distributions of box office revenue and production budget show a high degree of similarity between leaked and unleaked films, demonstrating no statistically significant difference in the median values of these variables.

We employ a fixed-effects logistic regression to quantify the association of the independent

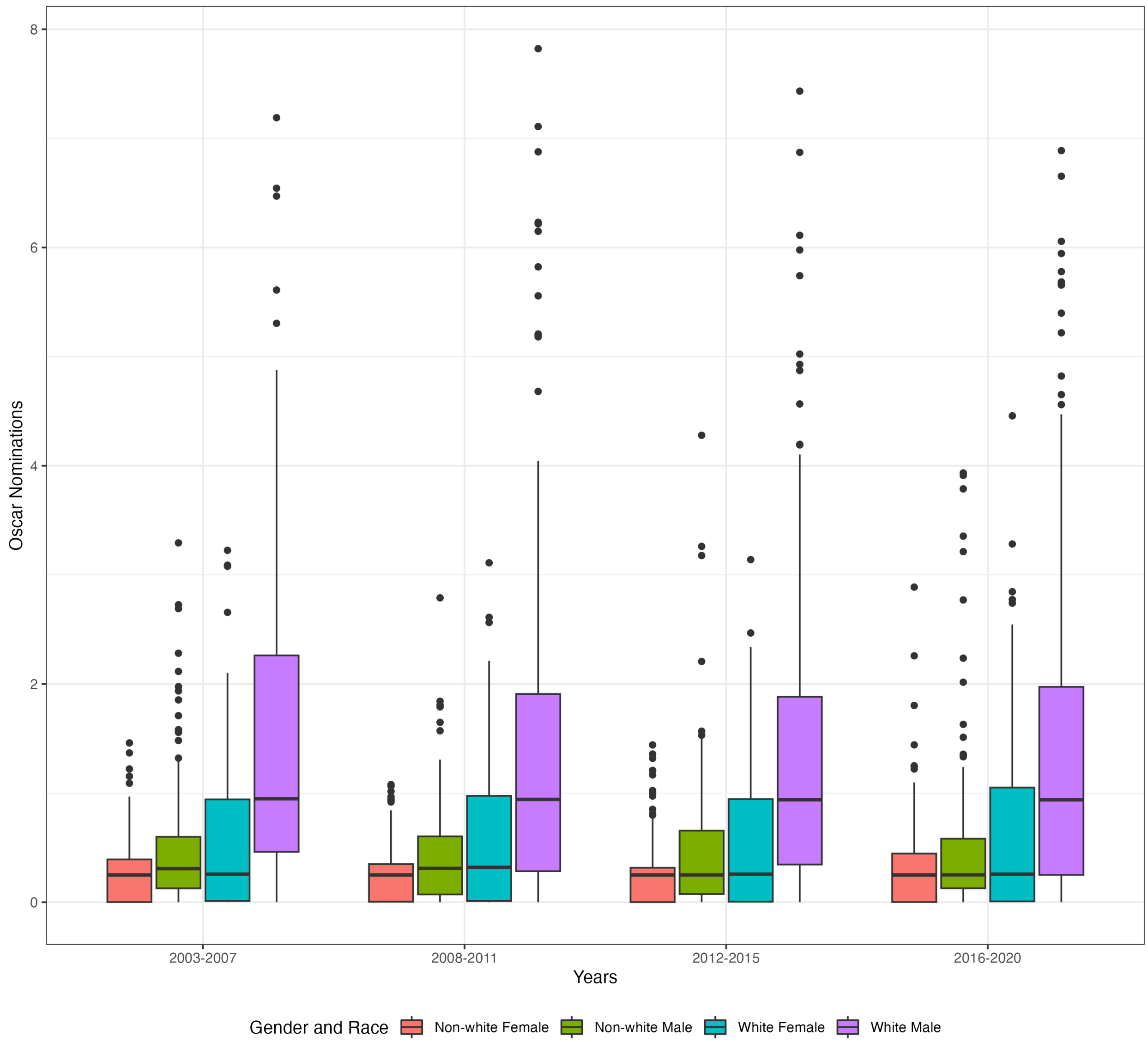
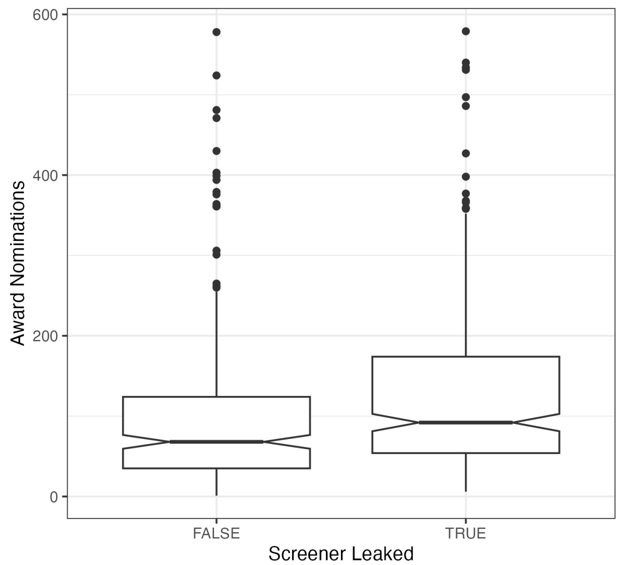
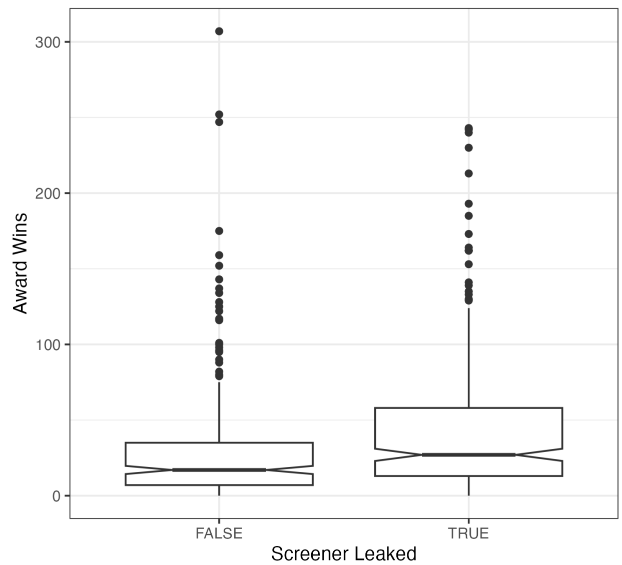


Figure 1: Gender and Race Representation Over Time

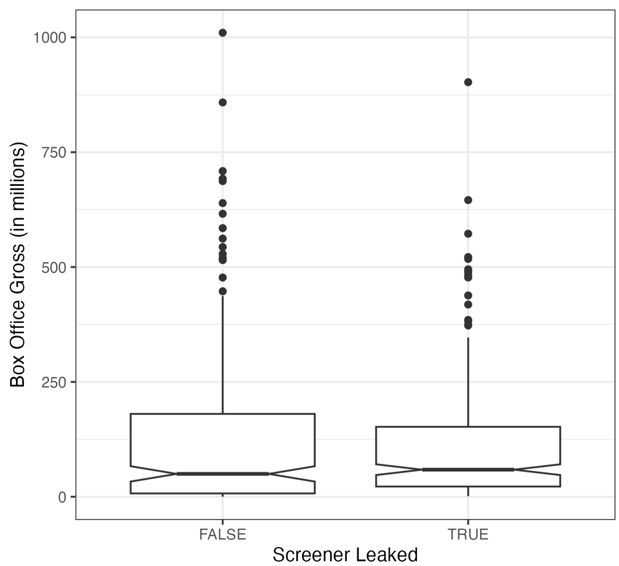
Note: Nominations are quantified as counts. Each set of plots corresponds to a distinct time period, with individual films as discrete data points. Each plot displays five key statistics: the median, the first and third quartiles (depicted by the hinges), and 1.5 times the interquartile range (the distance between the first and third quartiles), which is represented by the whiskers. Data points that lie beyond the interquartile range are plotted individually as outliers.



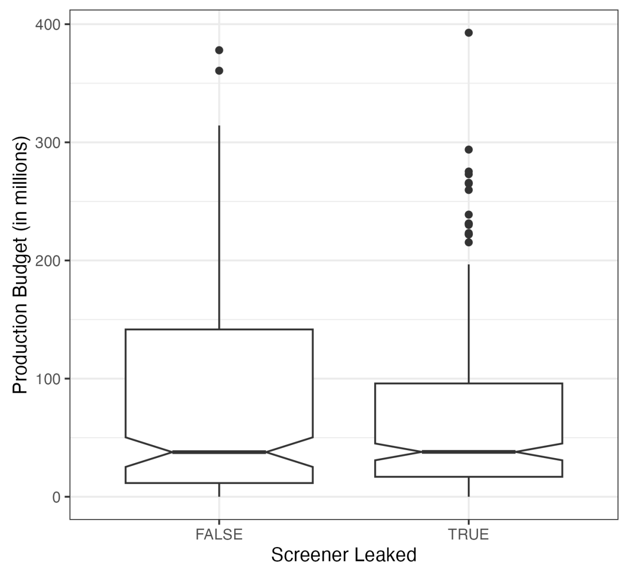
(a) Nominations



(b) Wins



(c) Box Office Gross



(d) Production Budget

Note: Award Nominations and Award Wins are represented as counts. Box Office Gross and Production Budget are measured in millions of 2020 US Dollars. Each film in the dataset serves as a data point. Each plot displays five key statistics: the median, the first and third quartiles (depicted by the hinges), and 1.5 times the interquartile range (the distance between the first and third quartiles), which is represented by the whiskers. Data points that lie beyond the interquartile range are plotted individually as outliers. The notches indicate the 95% confidence interval of the median.

Figure 2: Model Free Evidence – Artistic Excellence

variables with leaks in the four specified formats:

$$\text{Leak}^*_{fl} = \beta_{0l} + \beta_{1l}\text{Nominations}_f + \beta_{2l}\text{Budget}_f + \beta_{3l}\text{Box Office}_f + \sum_s \gamma_{sl} D_{sf} + \sum_y \delta_{yl} D_{yf} + \epsilon_f. \quad (1)$$

Here, Leak^*_{fl} is the latent variable representation of the binary dependent variable Leak_{fl}, which equals 1 if film f was leaked in format l and 0 otherwise. Nominations_f represents the count of award nominations received by film f, Budget_f signifies the film's production budget, and Box Office_f denotes the film's box office gross.

To account for studio-specific variations in technology, we include fixed effects, denoted by γ_{sl}, where D_{sf} is a dummy variable set to 1 if film f was produced by studio s. To address advancements in technology and shifts in piracy trends over time, we incorporate year-specific fixed effects δ_{yl}, with D_{yf} being a dummy variable that equals 1 if film f was nominated in year y. ϵ_f and the outside option are both distributed as independent and identically distributed (i.i.d.) Gumbel variables. The coefficients $\beta_{1l}, \beta_{2l}, \beta_{3l}$ capture the influence of each independent variable on the likelihood of a film being pirated. We employ a stringent p-value threshold of $p < 0.01$ to ensure a high level of statistical confidence.

Empirical Findings: Artistic Excellence

Table 2 shows a highly significant positive coefficient for 'Award Nominations' in predicting screener leaks (p-value = 5.42e-06). Each additional award nomination increases the log-odds of a screener leak by 0.005. 'Log-odds' in this context refers to the natural logarithm of the odds ratio, indicating the likelihood of a film's screener being pirated relative to not being pirated. On average, films in our data set have a leak probability of 53%. Therefore, such a film would experience a 0.12% increase in leak probability with each additional award nomination. Furthermore, with the number of award nominations in our data ranging from 1 to 579 and a mean of 113.88, this finding suggests that films with fewer nominations, unlike highly-nominated ones such as '12 Years a Slave,'

Table 2: Leak Determinants

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Nominations	$.005(.001)^{**}$	$.0002(.001)$	$-.002(.002)$	$.001(.001)$
Box Office Gross	$-.001(.001)$	$.002(.001)$	$.009(.002)^{**}$	$.001(.001)$
Production Budget	$-.003(.002)$	$.009(.003)^{**}$	$.016(.003)^{**}$	$.004(.002)$
Constant	$2.221(0.773)^{*}$	$-1.888(.660)^{*}$	$-.499(0.756)$	$-1.676(0.761)$
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−309.651	−252.369	−173.711	−260.324
Akaike Inf. Crit.	691.302	576.738	419.422	592.647

*p<0.01; **p<0.001

are much less likely to be pirated. This supports our thesis that films with high artistic quality, evidenced by numerous award nominations, face an elevated risk of screener piracy. However, 'Box Office Gross' and 'Production Budget' do not significantly influence screener leaks, indicating that factors related to commercial success are less relevant in this type of piracy.

Commercially successful films, particularly those with substantial budgets and broad audience appeal, are frequent targets in for-profit piracy. This is evidenced by the positive coefficients for 'Box Office Gross' (p-value $<$ 0.01 for both cam and telesync leaks) and 'Production Budget' (p-value $<$ 0.01 for telesync leaks). In contrast, the coefficient on 'Award Nominations' is nonsignificant.

These findings are corroborated by data from Muso, a leading analytics firm in the media sector that monitors piracy trends across various platforms including streaming, torrents, web downloads, and stream-ripping. Muso's data indicates that the top 10 most pirated movies globally in 2022 were 'Spider-Man: No Way Home', 'The Batman', 'Doctor Strange in the Multiverse of Madness', 'Thor: Love and Thunder', 'Black Adam', 'Uncharted', 'Eternals', 'Top Gun: Maverick', 'Jurassic World Dominion', and 'Encanto'—all of which are big-budget blockbusters. According to The Numbers, a well-known database for movie financials, these films rank 53rd, 65th, 61st, 23rd, 79th, 346th, 81st, 152nd, 167th, and 235th, respectively, on the all-time movie production budget chart. Thus, for-profit piracy, through cam and telesync leaks, targets mainstream films with high consumer demand.

In contrast, piracy in alternative channels, such as streaming services and high-definition televisions, as depicted in the 'Other' category of Table 2, does not show a consistent pattern. The coefficients for all variables in this category are nonsignificant, suggesting a more opportunistic than systematic approach to piracy in these channels.

Robustness Checks

To ensure the robustness and reliability of our findings, we conducted eight additional analyses:

1. **Exclusion of All Studio Fixed Effects**: We reran the models without studio fixed effects to ensure that our results were not driven by a reduction in the degrees of freedom from the inclusion of these effects.
2. **Inclusion of All Studio Fixed Effects**: Our primary models only include fixed effects for the 16 studios that produced at least 10 Oscar-nominated films. We expanded the scope to include fixed effects from all 66 studios to ensure a more comprehensive evaluation.
3. **Substitution of Nominations with Wins**: Our data shows a significant and high correlation (0.92) between wins and nominations. Therefore, we did not include wins as an independent variable in the original models. We ran a version of our model where we substituted wins for nominations to ensure robustness to the choice of independent variable.
4. **Limited Dependent Variable Model**: We estimated a probit model to ensure robustness to our use of the logit model.
5. **Removal of Oscar Nominations**: Despite the temporal precedence of the voting process, we removed Oscar nominations from our award nominations variable to mitigate concerns of reverse causality.
6. **Addition of Critics' Ratings**: We included a variable that combines critics' ratings from Metacritic's Metascore and Rotten Tomatoes' Tomatometer. Critics' ratings were not significant for any of the four variables, implying that critics' views do not affect the likelihood of

films leaking given award nominations, box office gross, and production budget.

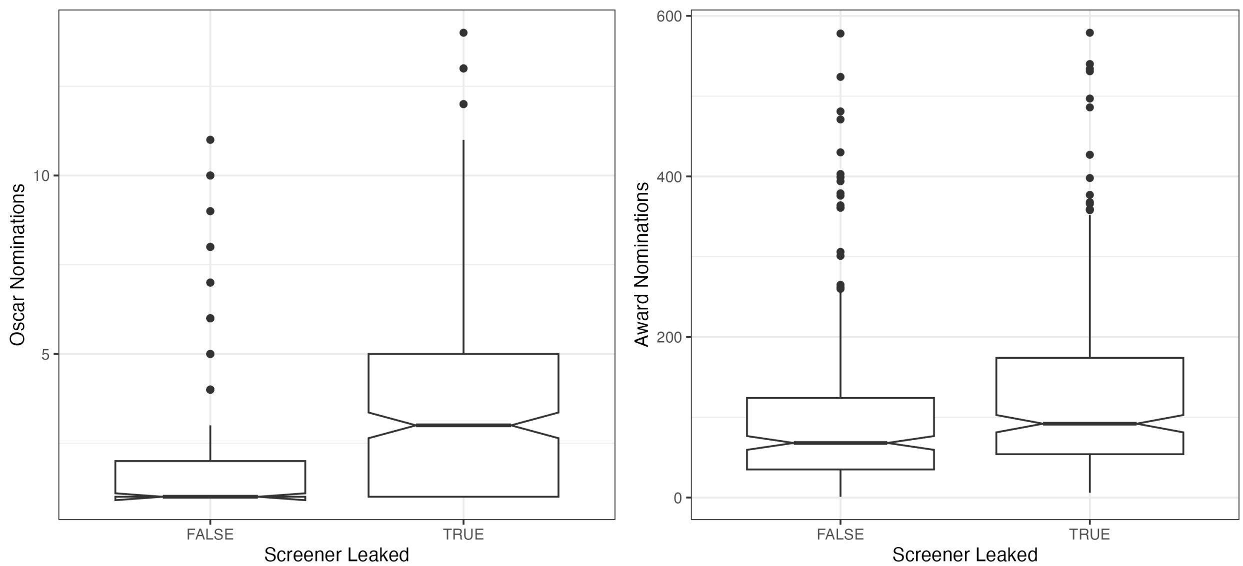
7. **Incorporation of Genre**: We used a multi-membership factor model to account for films associated with multiple genres. Out of the 84 genre coefficients, only 2 were significant, leaving 82 as nonsignificant. This suggests that the occurrence of film leaks does not vary across genres.
8. **Integration of User Ratings**: We included two additional measures of a film's popularity: the number (volume) and average (valence) of user ratings from IMDb. Both coefficients were nonsignificant in all four regression models.

Comprehensive results are detailed in Web Appendix A1. Across these analyses, we found that screener leaks are associated with artistic quality (i.e., award nominations). Cam and telesync leaks are associated with commercial success (i.e., production budget and box office gross). These associations remained statistically significant at the 0.01 level. The only notable variation arose in robustness check #7, where the p-value for the coefficient associated with production budget in cam leaks increased to 0.072. This change can be attributed to model saturation, induced by the inclusion of 21 nonsignificant genre fixed effects. Collectively, these various analyses reinforce the reliability of our primary findings.

Model-Free Evidence: Gender and Race

We now direct our analysis towards the impact of gender and race on the intersection of artistic excellence and film piracy. We begin by reevaluating the relationship between nominations and screener leaks. Figure 3 illustrates this relationship. The left panel displays the number of Oscar nominations for each film, while the right panel shows the aggregate nominations from all awards. Regardless of the metric used, leaked films consistently exhibit a significantly higher number of nominations, as evidenced by the non-overlapping 95% confidence intervals of the median values.

We developed analogous box plots, breaking down Oscar nominations by gender (female and male) and race (non-white and white) across four distinct variables. Figure 4 consists of four panels, each representing the count of Oscar nominees per Oscar-nominated film, differentiated by race and



(a) Oscar Nominations

(b) All Nominations

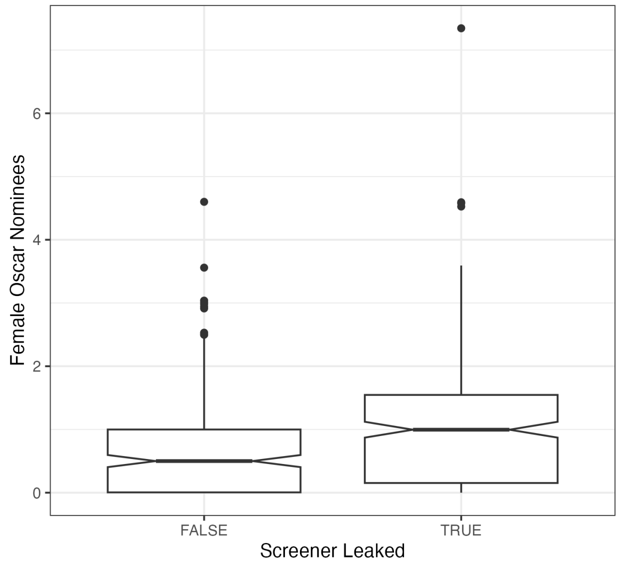
Note: Nominations are represented as counts. Each film in the dataset serves as a data point. Each plot displays five key statistics: the median, the first and third quartiles (depicted by the hinges), and 1.5 times the interquartile range (the distance between the first and third quartiles), which is represented by the whiskers. Data points that lie beyond the interquartile range are plotted individually as outliers. The notches indicate the 95% confidence interval of the median.

Figure 3: Model Free Evidence – Oscar Nominations

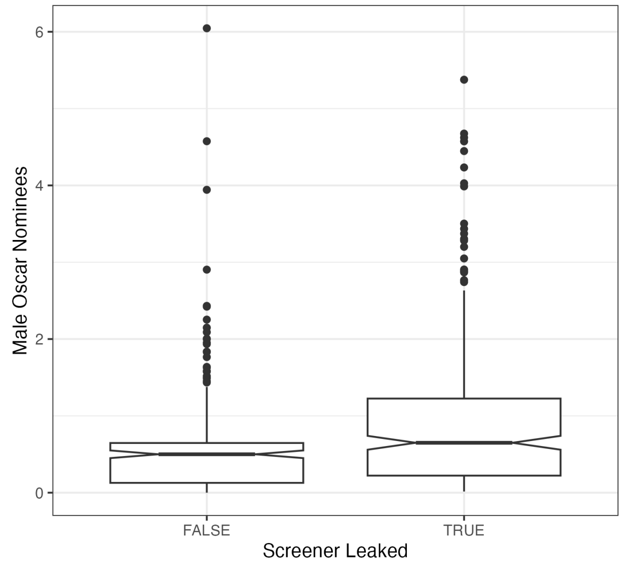
gender and further subdivided into categories of leaked and non-leaked films. We observe that the patterns in Figure 3a are predominantly driven by the number of female Oscar nominees (top-left panel, Figure 4a) and the number of white Oscar nominees (bottom-right panel, Figure 4d). These visualizations suggest variations in the probability of an Oscar screener leak across gender and race groupings.

Empirical Findings: Gender and Race

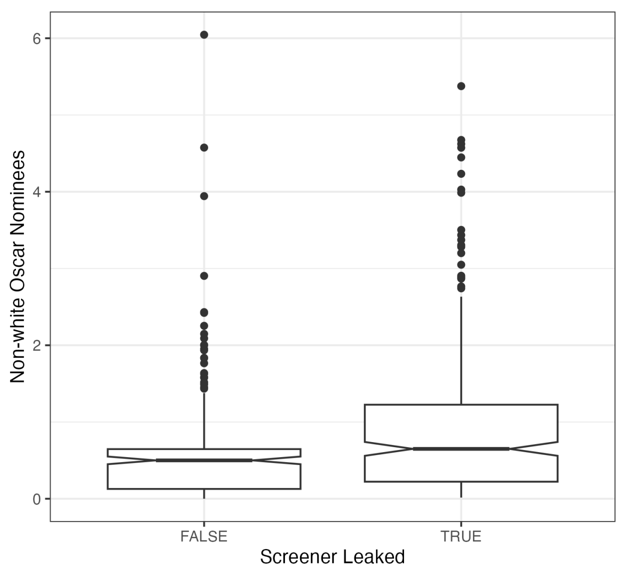
We use a fixed-effects logistic regression model to investigate the relationship between film piracy and the representation of gender and race among Oscar nominees. The formal representation of this



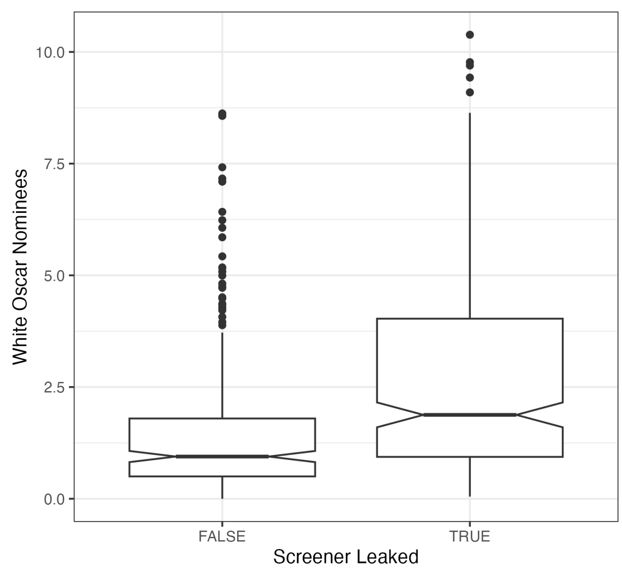
(a) Female Nominees



(b) Male Nominees



(c) Non-white Nominees



(d) White Nominees

Note: Nominations are represented as counts. Each film in the dataset serves as a data point. Each plot displays five key statistics: the median, the first and third quartiles (depicted by the hinges), and 1.5 times the interquartile range (the distance between the first and third quartiles), which is represented by the whiskers. Data points that lie beyond the interquartile range are plotted individually as outliers. The notches indicate the 95% confidence interval of the median.

Figure 4: Oscar Nominations – Gender and Race-Based

relationship is as follows:

$$
\begin{aligned}
\text{Leak}^*_{fl} = \beta_{0l} &+ \beta_{1wfl}\text{Nominations White Female}_f + \beta_{1wml}\text{Nominations White Male}_f \\
&+ \beta_{1nfl}\text{Nominations Non-white Female}_f + \beta_{1nml}\text{Nominations Non-white Male}_f \\
&+ \beta_{2l}\text{Budget}_f + \beta_{3l}\text{Box Office}_f + \sum_s \gamma_{sl} D_{sf} + \sum_y \delta_{yl} D_{yf} + \epsilon_f. \quad (2)
\end{aligned}
$$

In this model, each 'Nominations' variable symbolizes the count of Oscar nominees for a particular film f, classified by race and gender (that is, 'white female,' 'white male,' 'non-white female,' and 'non-white male' nominees). The corresponding regression coefficients for the categories 'white female,' 'white male,' 'non-white female,' and 'non-white male' are denoted as $\beta_{1wfl}, \beta_{1wml}, \beta_{1nfl}, \beta_{1nml}$, respectively.

Table 3: Oscar Nominations and Leaks

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Oscar Nominees	$.276(.047)^{**}$	$-.007(.042)$	$-.089(.053)$	$.004(.045)$
Box Office Gross	$-.001(.001)$	$.002(.001)$	$.008(.002)^{**}$	$.001(.001)$
Production Budget	$-.003(.002)$	$.009(.003)^{**}$	$.016(.003)^{**}$	$.004(.002)$
Constant	$2.070(.772)^{*}$	$-1.864(.663)^{*}$	$-.406(.764)$	$-1.644(.762)$
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−299.694	−252.366	−173.190	−260.570
Akaike Inf. Crit.	671.387	576.733	418.380	593.139

*p<0.01; **p<0.001

We estimate four nested models to evaluate the role of gender and race-specific factors. Model 1 assumes uniform impact across gender and race by setting all gender- and race-based nomination coefficients to be equal ($\beta_{1wfl} = \beta_{1wml} = \beta_{1nfl} = \beta_{1nml}$). This model assesses the overarching effect of Oscar nominations on screener piracy. As illustrated in Table 3, our findings indicate that an incremental Oscar nomination is associated with a higher likelihood of screener leaks. Consistent with our prior findings, Oscar nominations are not significantly related to cam leaks, telesync leaks, or other types of leaks.

For Models 2, 3, and 4, we introduce gender and race-specific coefficients. Specifically, Model 2 sets $\beta_{1wfl} = \beta_{1wml}$ and $\beta_{1nfl} = \beta_{1nml}$. Model 3 sets $\beta_{1wfl} = \beta_{1nfl}$ and $\beta_{1wml} = \beta_{1nml}$. Model 4 estimates the four gender and race-specific coefficients without imposing any restrictions. To conserve space, the results for Models 2 and 3 are provided in Web Appendix A2. Table 4 presents the results for Model 4. Table 5 consolidates the findings from Models 1, 2, 3, and 4 for screener leaks.

Table 4: Oscar Nominations and Leaks: Results by Gender and Race

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Gender and Race				
Female White	.798 (.226)**	−.178 (.220)	−.145 (.284)	−.251 (.228)
Male White	.251 (.092)*	.152 (.093)	−.014 (.123)	.019 (.094)
Female Non-white	−.311 (.489)	.480 (.521)	.245 (.685)	−.004 (.518)
Male Non-white	.176 (.257)	−.544 (.265)	−.428 (.348)	.206 (.263)
Box Office Gross	−.001 (.001)	.002 (.001)	.008 (.002)**	.001 (.001)
Production Budget	−.003 (.002)	.009 (.003)**	.016 (.003)**	.003 (.002)
Constant	2.002 (.779)	−1.843 (.669)*	−.338 (.784)	−1.571 (.766)
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−296.526	−249.824	−172.663	−259.277
Akaike Inf. Crit.	671.052	577.648	423.326	596.553

*p<0.01; **p<0.001

The gender-focused regression for screener leaks, as shown in Web Appendix A2, displays significant and positive coefficients for both female and male nominees. The magnitude of the coefficient for female nominees is greater, although the difference is not statistically significant. The race-focused regression for screener leaks, detailed in Web Appendix A2, reveals a significant,

Table 5: Oscar Nominations and Screener Leaks: All Models

	ScreenerLeak:			
	(1)	(2)	(3)	(4)
All	.276(.047)**			
Gender				
Female		.473(.129)**		
Male		.206(.062)**		
Race				
White			.347(.082)**	
Non-white			.095(.175)	
Gender and Race				
Female White				.798(.226)**
Male White				.251(.092)*
Female Non-white				−.311(.489)
Male Non-white				.176(.257)
Other covariates				
Box Office Gross	−.001(.001)	−.001(.001)	−.001(.001)	−.001(.001)
Production Budget	−.003(.002)	−.003(.002)	−.003(.002)	−.003(.002)
Constant	2.070(.772)*	2.007(.774)*	2.084(.772)*	2.002 (.779)
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−299.694	−298.286	−299.125	−296.526
Akaike Inf. Crit.	671.387	670.571	672.249	671.052

Note: *p<0.01; **p<0.001

positive coefficient for white nominees but a nonsignificant coefficient for non-white nominees. In all other regressions, neither the gender- nor the race-specific nominee coefficients are statistically significant.

Table 4 presents results from the full model, which indicate a strong association between white female nominees and screener leaks and a weaker but still significant association for white male nominees. Notably, the coefficients for these two groups are statistically different at the 5% level ($p = 0.0298$). As with prior analyses, no associations are found between Oscar nominations and other types of leaks.

These results suggest that the intersection of race and gender influences the probability of screener leaks. This is consistent with in-group favoritism prompting altruistic behaviors toward members with similar racial and gender identities. Interestingly, coefficients for non-white nominees are nonsignificant across all specifications. For example, in the full model, the coefficients for female and male non-white nominees exhibit p-values of 0.492 and 0.525, respectively.

For context, consider a film with a base screener leak probability of 53%, the average in our dataset. An additional Oscar nomination for a white female nominee increases the log-odds by 0.798, translating to a leak probability of 71.4%–an increase of 18.4%. While the impact of each additional nomination is bounded by 1 and depends on the film's existing probability, the key takeaway is that the effect of Oscar nominations on screener leaks varies significantly with respect to gender and race.

Robustness Checks

We conducted the same robustness checks as in our previous analyses, albeit with two notable modifications. First, the analysis excluding Oscar nominations was irrelevant, as we substituted this variable with gender- and race-specific counts of Oscar nominees. Second, the scarcity of data on Oscar wins precludes its analysis; 68% of the observations have zero values for the focal variables, indicating the films did not secure an Oscar win.

The outcomes of these robustness tests are detailed in Web Appendix A3. Across all six checks, our core conclusions remain robust, with two significant deviations. First, when genre fixed effects are incorporated into the model, the coefficient for the production budget in the cam leaks regression attains marginal significance at the 10% level ($p = 0.075$). Secondly, the coefficient for white male nominees in the screener leaks regression becomes statistically significant at the 5% level ($p = 0.035$). These models, however, become saturated under such conditions. Notably, only 2 out of the 84 genre coefficients achieve statistical significance across the four regressions. Furthermore, all 21 coefficients in the cam leaks regression lack significance, reinforcing the notion that film leak probabilities are not significantly influenced by genre. This observation justifies our choice of employing a more parsimonious model in our primary analysis.

Consistent with our earlier findings, neither the average user rating nor the volume of user reviews—commonly used indicators of film popularity—exhibit a discernible impact on screener leaks. These results further substantiate our central thesis: screener leaks are more strongly associated with films' artistic excellence rather than their commercial appeal. This association is notably absent in cam and telesync leaks, emphasizing the distinct motivations driving different types of film piracy.

Discussion

Our study makes three key contributions to the literature. First, we offer a novel, non-financial perspective on the study of piracy, challenging the conventional wisdom that solely financial motives drive this illicit activity. Second, we present empirical findings that reveal gender- and race-specific biases in Oscar screener leaks, broadening the discussion to include social biases. Third, we introduce an innovative, intersectional methodology designed to generate insights into phenomena that are often difficult to study due to limited data availability. Together, these contributions serve to expand our understanding of intellectual property piracy within the context of the entertainment industry, particularly in the unique case of Oscar screener leaks.

We uncover a consistent positive relationship between a film's artistic excellence and its vulnerability to Oscar piracy. Importantly, this relationship does not extend to commercial success, thus distinguishing Oscar screener piracy from traditional for-profit piracy. Our results also reveal a significant relationship between the number of white female and white male nominees and the propensity for screener leaks. These results highlight the complex interplay of artistic quality, gender, and race in piracy occurrences. Moreover, the chronological sequencing of our independent variables, established prior to the data collection period, enhances the robustness of our findings. By focusing on post-theatrical piracy, we are able to include summary measures from both the pre-theatrical and theatrical phases of the film release cycle. These measures provide a comprehensive account of the influence of film-specific factors, such as the production team, actors, and plot, thereby bolstering the reliability of our conclusions. Nevertheless, the observational nature of our data necessitates cautious interpretation of our findings.

Implications. The discovery that non-financial motivations significantly influence intellectual property piracy extends beyond the realm of the film industry, carrying profound implications for the broader political economy of intellectual property rights (Sun, Easley, and Kim 2015). It challenges conventional regulatory frameworks and industry strategies, such as staged content availability, by highlighting the complex interplay of ethical considerations in copyright enforcement across various artistic domains, including art, music, and literature (Ginsburg 2001; Ma et al. 2014).

Furthermore, our findings underscore the pivotal role of gender and race in the dynamics of intellectual property piracy, contributing to a nuanced understanding of 'cultural capital' within the Academy. This aspect of our research not only delineates the differential impact of Academy members' actions on films featuring artists from diverse genders and races but also reflects broader societal structures of privilege and power. Such disparities emphasize the urgency of moving from mere recognition of underrepresentation to active measures promoting inclusivity in the creative industries.

A paradox emerges when considering the repercussions of leaks. A leak facilitates a film's immediate entry into global piracy circuits, thereby boosting its illegal availability and visibility.

However, it also jeopardizes revenues from post-theatrical channels such as Blu-ray sales and streaming, which may curtail the film's future legal availability and reduce 'residuals,' payments made to performers beyond their initial compensation (Bai and Waldfogel 2012; Smith and Telang 2016). When examined through the intersections of gender and race, these consequences highlight that the implications of our findings for diversity, inclusion, and equity are far from unambiguous.

Limitations and Future Research Like most research on illicit activities, our study relies on observational data, which has inherent constraints. Considering experimental designs as an alternative reveals several challenges, especially since participants would be engaging in illegal activities. Even with informed consent, obtaining ethical approval from institutional review boards is unlikely. Potential legal ramifications could deter participation and expose both subjects and researchers to significant risks. Experimental manipulation of illegal behaviors may distort the natural conditions under which they occur, reducing external validity. Furthermore, obtaining truthful admissions about undetected illegal activities presents obstacles, as perpetrators are unlikely to confess openly. Consequently, experimental accounts of crime are rare and tend to be qualitative and much more limited in scope and generalizability (Venkatesh et al. 2008).

Gathering direct evidence about the drivers of illicit actions is especially challenging when dealing with a group as large, elusive, and influential as the Academy. Access to its elite membership is highly restricted, making research difficult. As a result, most existing evidence on intellectual property piracy, and illegal activities in general, primarily pertains to less powerful individuals, such as online consumers (Danaher and Smith 2014). Very few studies have been conducted on the suppliers of pirated content, and none have focused on industry insiders. In contrast, our study investigates the activities of the most influential figures in the entertainment industry—household names who risk their reputations and face legal consequences, despite minimal personal gain from engaging in piracy.

While this study provides important evidence on the non-financial motivations behind Oscar screener leaks, significant opportunities remain for future research. Developing creative methodologies that ethically examine motivations through interviews or surveys could prove insightful. Technological advancements may enable more sophisticated data collection, overcoming current constraints. Partnerships facilitating access while ensuring privacy could also be explored. Most crucially, more work is needed to unpack the paradox of leaks promoting diversity yet potentially compromising revenue streams supporting marginalized groups. This complex interplay between cultural benefits and economic impacts underscores the need for nuanced intellectual property policies that balance artistic access and financial sustainability. Overall, our findings highlight rich avenues for further investigating the multifaceted drivers of media piracy and informing equitable industry practices.

Robustness Checks: Artistic Excellence

The manuscript offers model-free evidence and regression analyses to show that artistic excellence, gauged by award nominations, is positively associated with screener leaks. In contrast, commercial appeal, as indicated by production budget and box office gross, is positively associated with cam and telesync leaks. These divergent relationships lend initial empirical support to our hypothesis that screener leaks are motivated by non-financial factors, while cam and telesync leaks are profit-driven.

In this section, we present detailed results from eight robustness checks conducted to validate core findings. These checks assess the stability of our results under varied model assumptions and variable definitions:

1. Exclusion of all studio fixed effects
2. Inclusion of all studio fixed effects
3. Replacement of nominations with wins
4. Limited dependent variable model
5. Exclusion of Oscar nominations
6. Addition of critics' ratings
7. Inclusion of genre
8. Integration of user ratings

Across these checks, the key relationships between leak types and artistic or commercial factors remain statistically significant, corroborating the robustness of our main analysis. Comprehensive results are tabulated below.

Exclusion of All Studio Fixed Effects

Table A1: Robustness Check, Exclusion of All Studio Fixed Effects

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Nominations	$.005(.001)^{**}$	$-.0004(.001)$	$-.003(.002)$	$.0004(.001)$
Box Office Gross	$-.001(.001)$	$.003(.001)$	$.010(.002)^{**}$	$.001(.001)$
Production Budget	$-.002(.002)$	$.013(.002)^{**}$	$.017(.003)^{**}$	$.004(.002)$
Constant	$1.927(.629)^{*}$	$-2.635(.525)^{**}$	$-1.238(.522)$	$-2.660(.638)^{**}$
Distributor	No	No	No	No
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−318.518	−272.756	−191.091	−278.869
Akaike Inf. Crit.	679.035	587.512	424.183	599.739
Note:				*p<0.01; **p<0.001

Inclusion of All Studio Fixed Effects

Table A2: Robustness Check, Inclusion of All Studio Fixed Effects

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Nominations	$.005(.001)^{**}$	$.002(.001)$	$-.002(.002)$	$.001(.001)$
Box Office Gross	$-.001(.001)$	$.001(.001)$	$.009(.002)^{**}$	$.001(.001)$
Production Budget	$-.004(.002)$	$.009(.003)^{*}$	$.015(.003)^{**}$	$.003(.003)$
Constant	$2.487(.812)^{*}$	$-1.907(.665)^{*}$	$-.202(.774)$	$-1.610(.763)$
Distributor	Extended	Extended	Extended	Extended
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−267.421	−219.842	−161.410	−232.934
Akaike Inf. Crit.	706.841	611.685	494.819	637.868
Note:				*p<0.01; **p<0.001

Substitution of Nominations with Wins

Table A3: Robustness Check, Substitution of Nominations with Wins

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Wins	$.010(.003)^{**}$	$.001(.003)$	$-.008(.004)$	$.004(.003)$
Box Office Gross	$-.0004(.001)$	$.002(.001)$	$.009(.002)^{**}$	$.001(.001)$
Production Budget	$-.003(.002)$	$.009(.003)^{**}$	$.015(.003)^{**}$	$.004(.002)$
Constant	$2.354(.771)^{*}$	$-1.891(.657)^{*}$	$-.534(.762)$	$-1.669(.758)$
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−313.344	−252.284	−172.617	−259.776
Akaike Inf. Crit.	698.688	576.569	417.233	591.551
Note:				*p<0.01; **p<0.001

Limited Dependent Variable Model

Table A4: Robustness Check, Limited Dependent Variable Model

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Nominations	$.003(.001)^{**}$	$.0001(.001)$	$-.001(.001)$	$.001(.001)$
Box Office Gross	$-.0004(.001)$	$.001(.001)$	$.005(.001)^{**}$	$.001(.001)$
Production Budget	$-.002(.001)$	$.005(.001)^{**}$	$.009(.002)^{**}$	$.002(.001)$
Constant	$1.280(.422)^{*}$	$-1.070(.383)^{*}$	$-.259(.428)$	$-1.044(.428)$
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−309.096	−253.965	−173.886	−260.691
Akaike Inf. Crit.	690.192	579.930	419.773	593.381
Note:				*p<0.01; **p<0.001

Removal of Oscar Nominations

Table A5: Robustness Check, Removal of Oscar Nominations

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Nominations	$.003(.001)^{**}$	$.0001(.001)$	$-.001(.001)$	$.001(.001)$
Box Office Gross	$-.0003(.001)$	$.001(.001)$	$.005(.001)^{**}$	$.001(.001)$
Production Budget	$-.002(.001)$	$.005(.001)^{**}$	$.009(.002)^{**}$	$.002(.001)$
Constant	$1.284(.422)^{*}$	$-1.070(.383)^{*}$	$-.261(.428)$	$-1.045(.428)$
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−309.455	−253.964	−173.906	−260.682
Akaike Inf. Crit.	690.910	579.927	419.812	593.364
Note:				*p<0.01; **p<0.001

Addition of Critics' Ratings

Table A6: Robustness Check, Addition of Critics' Ratings

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Nominations	$.005(.001)^{**}$	$.001(.001)$	$-.002(.002)$	$.001(.001)$
Box Office Gross	$-.001(.001)$	$.002(.001)$	$.009(.002)^{**}$	$.001(.001)$
Production Budget	$-.003(.002)$	$.009(.003)^{**}$	$.016(.003)^{**}$	$.004(.003)$
Critics' Ratings	$-.002(.008)$	$-.007(.009)$	$.0002(.011)$	$.005(.010)$
Constant	$2.328(.976)$	$-1.423(.938)$	$-.514(1.122)$	$-2.041(1.021)$
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−309.635	−252.127	−173.711	−260.178
Akaike Inf. Crit.	693.269	578.255	421.422	594.356
Note:				*p<0.01; **p<0.001

Incorporation of Genre

Table A7: Robustness Check, Incorporation of Genre

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Nominations	.005(.001)**	.001(.001)	−.001(.002)	.002(.001)
Box Office Gross	.0003(.001)	.002(.001)	.008(.002)**	−.0001(.001)
Production Budget	.003(.003)	.006(.003)	.015(.004)**	.001(.003)
Genre				
Action	−.525(.375)	.416(.401)	1.043(.525)	1.026(.401)
Adventure	−.556(.409)	.746(.442)	.061(.559)	−.295(.425)
Animation	−.366(.435)	.023(.478)	1.088(.595)	−.049(.422)
Biography	.469(.330)	.119(.376)	.534(.537)	.374(.374)
Comedy	.020(.330)	−.160(.388)	.730(.538)	.675(.372)
Crime	−.064(.378)	.860(.420)	1.130(.593)	.300(.421)
Drama	.528(.406)	−.692(.453)	−.517(.564)	−.805(.417)
Family	−1.176(.532)	.964(.568)	2.188(.673)*	.170(.511)
Fantasy	−.304(.493)	−.616(.563)	−.627(.790)	.712(.523)
History	.473(.463)	.919(.497)	−.548(.791)	−.713(.523)
Horror	−1.059(1.499)	1.635(1.553)		−.386(1.521)
Music	−.514(.539)	.148(.571)	1.408(.827)	−.029(.630)
Musical	.544(1.048)	−.027(1.053)	−.442(1.314)	−.070(1.425)
Mystery	−.609(.468)	.422(.496)	.705(.661)	.433(.543)
News	.248(1.884)	1.877(2.006)		.869(1.590)
Romance	−.250(.354)	.060(.429)	.627(.560)	−.480(.433)
Sci-Fi	−1.535(.500)*	.367(.524)	1.661(.684)	.329(.485)
Sport	−.122(1.065)	1.053(1.019)	−.580(1.388)	−.627(1.293)
Thriller	−.541(.418)	−.067(.491)	.649(.604)	.725(.461)
War	.611(.758)	.234(.844)	.171(1.580)	.722(.983)
Western	.330(1.661)	−.387(1.741)	3.096(2.195)	
Constant	2.375(.997)	−2.079(.963)	−1.388(1.271)	−1.466(1.016)
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−284.670	−238.235	−154.820	−244.352
Akaike Inf. Crit.	683.339	590.470	419.639	600.704

Note: *p<0.01; **p<0.001

Integration of User Ratings

Table A8: Robustness Check, Integration of User Ratings

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Award Nominations	$.005(.001)^{**}$	$-.0004(.001)$	$-.003(.002)$	$-.001(.001)$
Box Office Gross	$.0001(.001)$	$.001(.002)$	$.008(.002)^{**}$	$-.0004(.001)$
Production Budget	$-.002(.002)$	$.008(.003)^{*}$	$.015(.003)^{**}$	$.003(.003)$
Average User Rating	$.439(.235)$	$-.429(.252)$	$-.269(.293)$	$.003(.250)$
Number of User Ratings	$-.001(.001)$	$.001(.001)$	$.001(.001)$	$.001(.001)$
Constant	$-.832(1.822)$	$1.083(1.890)$	$1.383(2.195)$	$-1.835(1.921)$
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−307.206	−249.928	−172.405	−256.537
Akaike Inf. Crit.	690.412	575.857	420.811	589.075

Note: *p<0.01; **p<0.001

Intersectionality of Oscar Nominations, Race, and Gender

The main paper demonstrates that the relationship between a film's Oscar nominations and screener leaks is contingent on the gender and race of the nominees. Four nested models are estimated: The first assumes equal impact across all genders and races, the second and third introduce separate coefficients for gender and race, respectively, and the fourth includes distinct coefficients for white female, white male, non-white female, and non-white male nominees.

Our analysis reveals a significant positive association between white female nominees and screener leaks, with a weaker association for white male nominees. The coefficients for non-white nominees are statistically nonsignificant. These findings support the notion that the influence of Oscar nominations on screener leaks is intersectional, lending credibility to selective altruism as an underlying driver. To economize on space, this section provides detailed results for Models 2 and 3, while Models 1 and 4 are delineated in the main manuscript.

By Gender

Table A9: Oscar Nominations and Leaks: Results by Gender

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Gender				
Female	.473(.129)**	−.043(.126)	−.054(.179)	−.168(.132)
Male	.206(.062)**	.006(.061)	−.101(.080)	.066(.064)
Box Office Gross	−.001(.001)	.002(.001)	.008(.002)**	.001(.001)
Production Budget	−.003(.002)	.009(.003)**	.016(.003)**	.003(.002)
Constant	2.007(.774)*	−1.850(.664)*	−.431(.773)	−1.588(.765)
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−298.286	−252.321	−173.169	−259.617
Akaike Inf. Crit.	670.571	578.642	420.338	593.233

*p<0.01; **p<0.001

By Race

Table A10: Oscar Nominations and Leaks: Results by Race

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Race				
White	.347(.082)**	.096(.078)	−.032(.100)	−.037(.081)
Non-white	.095(.175)	−.278(.181)	−.253(.254)	.112(.184)
Box Office Gross	−.001(.001)	.002(.001)	.008(.002)**	.001(.001)
Production Budget	−.003(.002)	.009(.003)**	.016(.003)**	.004(.002)
Constant	2.084(.772)*	−1.889(.664)*	−.385(.766)	−1.637(.762)
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−299.125	−251.110	−172.966	−260.385
Akaike Inf. Crit.	672.249	576.219	419.932	594.769

*p<0.01; **p<0.001

Robustness Checks: Intersectionality of Oscar Nominations, Race, and Gender

In this section, we detail six robustness checks conducted on the model investigating the intersectionality of screener leaks with the race and gender of Oscar nominees:

1. Exclusion of all studio fixed effects
2. Inclusion of all studio fixed effects
3. Limited dependent variable model
4. Addition of critics' ratings
5. Incorporation of genre
6. Integration of user ratings

These checks confirm that the key relationships between the race and gender of Oscar nominees and the likelihood of screener leaks maintain statistical significance, substantiating the reliability of our primary findings. Comprehensive results are tabulated below.

Exclusion of All Studio Fixed Effects

Table A11: Robustness Check, Exclusion of all studio fixed effects

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Gender and Race				
Female White	.814 (.217)**	−.151 (.205)	−.236 (.254)	−.236 (.217)
Male White	.286 (.089)*	.185 (.089)	.007 (.112)	.018 (.089)
Female Non-white	−.382 (.476)	.268 (.489)	.071 (.616)	−.112 (.487)
Male Non-white	.149 (.249)	−.530 (.252)	−.336 (.312)	.202 (.244)
Box Office Gross	−.001 (.001)	.002 (.001)	.009 (.002)**	.001 (.001)
Production Budget	−.002 (.002)	.013 (.002)**	.017 (.003)**	.004 (.002)
Constant	1.722 (.638)*	−2.691 (.540)**	−1.142 (.537)	−2.556 (.643)**
Distributor	No	No	No	No
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−304.607	−269.737	−190.485	−277.391
Akaike Inf. Crit.	657.215	587.475	428.969	602.782

*p<0.01; **p<0.001

Inclusion of All Studio Fixed Effects

Table A12: Robustness Check, Inclusion of All Studio Fixed Effects

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Gender and Race				
Female White	.993 (.259)**	−.085 (.238)	−.131 (.297)	−.401 (.251)
Male White	.153 (.106)	.105 (.100)	−.073 (.130)	.005 (.103)
Female Non-white	−.486 (.565)	.215 (.557)	.311 (.718)	−.408 (.619)
Male Non-white	.503 (.338)	−.248 (.285)	−.312 (.359)	.404 (.294)
Box Office Gross	−.001 (.001)	.002 (.001)	.009 (.002)**	.002 (.001)
Production Budget	−.003 (.003)	.008 (.003)*	.016 (.003)**	.002 (.003)
Constant	2.218 (.828)*	−1.832 (.673)*	−.036 (.810)	−1.471 (.771)
Distributor	Extended	Extended	Extended	Extended
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−252.689	−219.989	−160.198	−229.492
Akaike Inf. Crit.	683.378	617.978	498.397	636.984

*p<0.01; **p<0.001

Limited Dependent Variable Model

Table A13: Robustness Check, Limited Dependent Variable Model

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Gender and Race				
Female White	.456 (.132)**	−.110 (.127)	−.080 (.160)	−.134 (.131)
Male White	.142 (.054)*	.081 (.054)	.002 (.068)	.018 (.054)
Female Non-white	−.147 (.287)	.315 (.300)	.160 (.382)	−.015 (.299)
Male Non-white	.115 (.149)	−.326 (.154)	−.242 (.194)	.111 (.154)
Box Office Gross	−.0004 (.001)	.001 (.001)	.004 (.001)**	.001 (.001)
Production Budget	−.002 (.001)	.005 (.001)**	.009 (.002)**	.002 (.001)
Constant	1.178 (.432)*	−1.043 (.388)*	−.179 (.442)	−.982 (.431)
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−296.035	−251.377	−173.027	−259.791
Akaike Inf. Crit.	670.069	580.754	424.053	597.583

$^{*}p<0.01$; $^{**}p<0.001$

Addition of Critics' Ratings

Table A14: Robustness Check, Addition of Critics' Ratings

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Gender and Race				
Female White	.797 (.227)**	−.172 (.221)	−.144 (.284)	−.263 (.229)
Male White	.250 (.094)*	.159 (.094)	−.011 (.124)	.006 (.096)
Female Non-white	−.311 (.489)	.477 (.522)	.245 (.685)	−.015 (.518)
Male Non-white	.176 (.258)	−.534 (.265)	−.425 (.349)	.196 (.264)
Box Office Gross	−.001 (.001)	.002 (.001)	.008 (.002)**	.001 (.001)
Critics' Ratings	.0003 (.008)	−.004 (.009)	−.002 (.010)	.007 (.009)
Production Budget	−.003 (.003)	.009 (.003)**	.016 (.003)**	.004 (.003)
Constant	1.984 (.967)	−1.553 (.915)	−.217 (1.106)	−2.091 (1.003)
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−296.526	−249.717	−172.651	−258.948
Akaike Inf. Crit.	673.051	579.433	425.302	597.895

*p<0.01; **p<0.001

Incorporation of Genre

Table A15: Robustness Check, Incorporation of Genre

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Female White	.715 (.239)*	−.072 (.240)	.243 (.344)	−.133 (.243)
Male White	.208 (.099)	.143 (.101)	.055 (.146)	.057 (.105)
Female Non-white	−.381 (.504)	.520 (.555)	.230 (.773)	−.154 (.553)
Male Non-white	.221 (.268)	−.471 (.289)	−.529 (.387)	.316 (.288)
Box Office Gross	.0001 (.001)	.002 (.001)	.008 (.002)**	.0002 (.001)
Production Budget	.003 (.003)	.005 (.003)	.015 (.004)**	.00002 (.003)
Genre				
Action	−.482 (.385)	.369 (.407)	1.147 (.535)	.980 (.405)
Adventure	−.695 (.414)	.695 (.445)	.129 (.560)	−.322 (.429)
Animation	−.159 (.443)	.063 (.485)	1.250 (.609)	−.178 (.432)
Biography	.253 (.336)	−.022 (.384)	.518 (.537)	.335 (.379)
Comedy	−.018 (.334)	−.222 (.390)	.743 (.541)	.690 (.373)
Crime	−.064 (.386)	.836 (.423)	1.168 (.594)	.294 (.425)
Drama	.427 (.411)	−.682 (.460)	−.426 (.581)	−.896 (.426)
Family	−1.199 (.544)	.942 (.568)	2.220 (.675)*	.158 (.512)
Fantasy	−.220 (.500)	−.566 (.568)	−.483 (.797)	.533 (.533)
History	.395 (.466)	.853 (.504)	−.771 (.802)	−.746 (.525)
Horror	−.876 (1.612)	1.540 (1.520)		−.349 (1.517)
Music	−.373 (.566)	1.084 (.576)	1.406 (.839)	−.106 (.634)
Musical	.157 (1.080)	.078 (1.057)	−.369 (1.336)	−.029 (1.447)
Mystery	−.706 (.480)	.339 (.501)	.695 (.667)	.405 (.540)
News	.023 (1.920)	1.748 (1.996)		.647 (1.588)
Romance	−.332 (.358)	.037 (.433)	.618 (.555)	−.468 (.435)
Sci-Fi	−1.438 (.506)*	.409 (.531)	1.779 (.701)	.266 (.492)
Sport	−.175 (1.111)	1.000 (1.048)	−.601 (1.395)	−.670 (1.310)
Thriller	−.407 (.434)	.032 (.500)	.801 (.617)	.660 (.463)
War	.149 (.771)	.257 (.858)	.368 (1.550)	.628 (.986)
Western	−.005 (1.774)	−.497 (1.774)	3.176 (2.300)	
Constant	2.422 (1.005)	−2.000 (.972)	−1.595 (1.290)	−1.268 (1.019)
Distributor & Year	Yes	Yes	Yes	Yes
Log Likelihood	−278.021	−236.760	−153.671	−243.604
Akaike Inf. Crit.	676.041	593.520	423.342	605.207

*p<0.01; **p<0.001

Integration of User Ratings

Table A16: Robustness Check, Integration of User Ratings

	Leak:			
	Screener	Cam	Telesync	Other
	(1)	(2)	(3)	(4)
Gender and Race				
Female White	.845 (.230)**	−.175 (.222)	−.119 (.287)	−.273 (.234)
Male White	.262 (.097)*	.140 (.097)	−.028 (.127)	−.050 (.101)
Female Non-white	−.384 (.494)	.502 (.526)	.213 (.689)	−.029 (.521)
Male Non-white	.198 (.261)	−.588 (.269)	−.468 (.350)	.164 (.265)
Box Office Gross	−.0001 (.001)	.001 (.001)	.007 (.002)**	−.0003 (.001)
Production Budget	−.002 (.003)	.008 (.003)*	.016 (.003)**	.003 (.003)
Average User Rating	.477 (.244)	−.439 (.255)	−.273 (.294)	−.021 (.254)
Number of User Ratings	−.001 (.001)	.001 (.001)	.001 (.001)	.001 (.001)
Constant	−1.279 (1.872)	1.184 (1.908)	1.548 (2.209)	−1.585 (1.948)
Distributor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	578	578	578	578
Log Likelihood	−293.886	−247.165	−171.519	−255.296
Akaike Inf. Crit.	669.771	576.330	425.037	592.592

*p<0.01; **p<0.001

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