UNIVERSITA’ COMMERCIALE “LUIGI BOCCONI”

PhD SCHOOL

PhD program in Business Administration and Management

Cycle: 32

Disciplinary Field (code): SECS-P/10

# Essays on Dynamics of Collaboration and Recognition in Hollywood Movie Industry

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**Year 2021**

**Stand up or stand by: Evidence of social networks and whistle-blowing in Hollywood**

ABSTRACT

Studies on whistle-blowing investigate how individual characteristics and contextual factors are related to probability of whistle-blowing. However, they do not explain how individuals leverage their network to engage in it. To explore this, we consider the incidents of whistle-blowing behaviors of sexual harassments in October 2017 in Hollywood. Whistle-blowing is very costly especially in Hollywood where social connections are crucial for achieving career success. Nevertheless, they decided to blow a whistle on sexual harassment. We explore who can be whistle-blowers and how network structure can amplify the probability and timing of whistle-blowing. We found that individual characteristics i.e., middle-age, social status, visibility, and media coverage can increase the probability of whistle-blowing. Also, high network status individuals and those are closer to previous whistle-blowers will be likely whistle-blowers. Moreover, by considering timing of whistle-blowing, individuals who are in open network will be early whistle-blowers while high-status individuals will be late whistle-blowers.

Keywords: Social network analysis, Whistle-blowing, Hollywood movie industry

# INTRODUCTION

On 5th October 2017, Jodi Kantor and Megan Twohey of The New York Times first reported that Ashley Judd, an American actress, accused American film producer Harvey Weinstein of sexual harassment (Kantor and Twohey 2017). Soon after this news article was published, more than 80 women in Hollywood including actresses such as Angelina Jolie, Mira Sorvino, and Gwyneth Paltrow subsequently accused Weinstein of sexual assault, rape, and harassment i.e., whistle-blowing. Harvey Weinstein is widely regarded as a powerful person in Hollywood (Ryan 2018), is one of the most thanked individuals in the history of the Oscars, and produces movies that have achieved immense commercial and critical success, e.g., Shakespeare in Love and the Lord of the Rings (Maroudi 2017). If young actresses work with him, they can receive recognition from their peers and thus achieve success in Hollywood. However, if they refuse his advances and demands, he can easily break their careers (Dry 2018). Hence, due to the risk of retaliation by Harvey Weinstein, some actresses may be forced to stay silent. Speaking up may destroy their career, so they cannot speak up. In this case, who is more likely to engage in whistle-blowing?

Whistle-blowing is a behavior that a former or current member of an organization discloses the illegal or unethical activities that occurred in the organization (Near and Miceli 1985). Most of the empirical research on whistle-blowing has focused on individual characteristics such as age, level of education, proactive personality, gender, and job performance (Dozier and Miceli 1985, Taylor and Curtis 2010, Vadera et al. 2013). Also, studies have examined contextual factors such as low severity of retaliation (Vadera et al. 2009), supportive bosses or friendly working environment (Miceli and Near 1984, Near and Miceli 1985), and supportive co-workers (Robinson and Kraatz 1998). Even though studies find that social relations influence whistle-blowing, it is not so clear how individuals leverage their network positions for their whistle-blowing and which network positions matter for early or late timing of whistle-blowing. Hence, this study examines how network positions amplify the probability of whistle-blowing and timing of whistle-blowing.

Our context is a series of incidents of sexual harassment of Harvey Weinstein in Hollywood movie industry. Network is very important in this industry (Bechky 2006). In Hollywood, individuals typically work in project organizations (Cattani and Ferriani 2008); after finishing one project they join a new project (Jones 1996). As each project needs creativity and efficient production routines (Levinthal and Madsen 2006), casting proper individuals in a project is particularly important in Hollywood. Moreover, people are willing to work with those who have been successful in the past since individual's talent is not transparent in creative industry (Rossman et al. 2010). If movie actors are associated with unfavorable impression/images, e.g., blacklisted actors, others try to avoid being associated with the movie actor (Pontikes et al. 2010). It is crucial for individuals in Hollywood to have a strong network to achieve success in this industry (Ferriani et al. 2009). Harvey Weinstein's accusers belong to this industry and are aware that network is important in this industry. If they engage in whistle-blowing, they may lose their job or jeopardize their career (Vadera et al. 2009). Nevertheless, they decided to blow a whistle on his sexual harassment. This situation is appropriate for explaining the struggles of individuals who suffer from sexual harassment by a powerful person.

To observe who can be whistle-blowers in this context, we include female whistle-blowers of Harvey Weinstein by 1st June 2018. For additional analysis, we also include more male sexual harassers and their female whistle-blowers. We collect data on movies released in the U.S. from 2015 to 2017. We also gather information on all casts of a movie, marital status, birth year of casts, producers, directors, writers, Oscar winner and nominees, and roles from IMDb. Additionally, we get data on Twitter followers from Twitter profiles of individuals and media coverage from Factiva. To identify who are whistle-blowers, we refer to three main sources: an article by USA TODAY on June 1, 2018, Asia Argento's twitter post, and an article by Vox on January 9th, 2019.

From our analysis, we found relationships between various individual characteristics and probability of whistle-blowing. In other words, individuals who are middle age, have high visibility (more Twitter followers), have won or got nominated Oscar, and received media coverage before whistle-blowing have high probability of whistle-blowing. We interpret our results as follows. First, older individuals might not consider the community carefully since they will likely finish their career soon. On the other hand, even if young individuals try to speak up, others might ignore their voice for reasons such as lack of legitimacy/reputation. Hence, middle-aged individuals have more probability of being whistle-blowers. Second, individuals who have high social status can get access to resources and recognition. Because of this, these individuals are more protected than others, so they will engage in whistle-blowing. Finally, individuals who have high visibility and receive more media coverage have enough attention from others. They can leverage attention from others for speaking up. Hence, they are more likely to be whistle-blowers.

We also examined how network variables (network status and geodesic distance between individuals and their previous whistle-blowers) determine probability. Individuals who have high network status i.e., eigenvector centrality, are more likely to be whistle-blowers. High network status indicates the level of popularity. By using this popularity and resources that come from their network positions, individuals with high network status can engage in whistle-blowing. Also, individuals who are closer to previous whistle-blowers are more likely to engage in whistle-blowing. If they are closer to previous whistle-blowers, they can easily observe previous whistle-blowers and notice that they can engage in whistle-blowing. Hence, we think they can be whistle-blowers.

Since whistle-blowing happened consequently after first whistle-blowers spoke up in this Hollywood context, we explore the diffusion of whistle-blowing contingent on individuals' network positions. As whistle-blowing occurred quickly in a short time i.e., mostly within 14 days, we consider early and late whistle-blowers to capture the diffusion process. We found that individuals who are in an open network are more likely to be early whistle-blowers while those who have high network status will be late whistle-blowers. We interpret that individuals in an open network can quickly realize the possibilities of whistle-blowing since they have information advantage (Burt 1992). Also, by spreading information broadly and effectively (González-Bailón & Wang, 2016), they can prepare for retaliation from the sexual harasser and create more negative publicity for this individual. On the other hand, individuals who have high network status might prefer the "wait and see" attitude when whistle-blowing is still very risky i.e., early timing of diffusion. If whistle-blowing is not accepted, other individuals might not work with the whistle-blower due to fear of bad impressions. If so, their popularity may go down; however, if more individuals become whistle-blowers and high-status individuals do not engage in whistle-blowing, then others may think that high network status individuals are lazy and/or incompetent. Hence, high network status individuals become late whistle-blowers.

We believe this study has several contributions to the literature on social network analysis and whistle-blowing. First, literature on whistle-blowing highlighted that social relations are related to probability of whistle-blowing. For example, when individuals perceive that they have support within organizations (Klaas et al. 2012, Lee et al. 2004, Miceli and Near 1984) and when retaliation is less severe due to coworkers' support (Rehg et al. 2008), they are more likely to engage in whistle-blowing. Even though these studies indicate that individuals receive relevant information from others, the link between social network and whistle-blowing is still missing. We can expect that some individuals have better positions to receive information and resources. We can also expect that some individuals can perceive the opportunities of whistle-blowing more quickly than others due to their network positions. Hence, it is worth observing how individuals leverage their network for whistle-blowing and how individuals follow previous whistle-blowers.

Second, this study explains the mechanisms of the diffusion of whistle-blowing and network positions. We find that closer distances between a focal actress and previous whistle-blowers can be a driver of whistle-blowing and that depending on the timing of whistle-blowing, different network positions can encourage individuals to speak up about sexual harassment.

Third, social network research has shown that network structure can facilitate or inhibit individuals' behavior (Burt et al. 2013) and final outcomes (Uzzi 1996). However, unlike other outcomes such as job performance or creativity, whistle-blowing itself is costly behavior. Because of this behavior, individuals may lose their job or cannot expect their promising career (Vadera et al. 2013). In this situation, it is crucial for whistle-blowers to exploit their social network and ties to get access to resources and spread their motivations and information to others. We can observe how individuals use their network in this risky situation in the context of whistle-blowing.

## RELATED LITERATURE

### Mechanism of whistle-blowing

Unethical behavior is defined as behavior or actions that are "either illegal or morally unacceptable to the larger community" (Jones, 1991: 367). Unethical behavior can include sexual harassment, which refers to "behavior that derogates, or humiliates an individual based on that individual's sex" (Berdahl, 2007: 644). When a harasser has more power than a target of sexual harassment, the harasser tends to engage in sexual harassment (Berdahl 2007, O'Leary-Kelly et al. 2009). Whistle-blowing is defined as "the disclosure by organization members (former or current) of illegal, immoral, or illegitimate practices under the control of their employers, to persons or organizations that may be able to effect action" (Near & Miceli, 1985: 4). In case of sexual harassment, victims of sexual harassment engage in whistle-blowing when they reveal details of their harassment and harasser.

Research has studied who can be whistle-blowers by considering individual characteristics and contextual factors (Mesmer-Magnus and Viswesvaran 2005, Vadera et al. 2009). Individual characteristics include job performance (Brewer and Selden 1998, Miceli and Near 1984, 2002), organizational position (Miceli and Near 1988), pay (Miceli and Near 1984), moral intensity (Chiu 2003, Taylor and Curtis 2010), and education (Miceli & Near, 1984). These characteristics are positively associated with probability of whistle-blowing. Research investigating the relationship between individual characteristics such as gender, age, and organizational tenure and whistle-blowing shows inconsistent findings (Mesmer-Magnus and Viswesvaran 2005, Sims and Keenan 1998, Stansbury and Victor 2009). Contextual factors consider the situation and condition of a whistle-blower. Individuals are more likely to engage in whistle-blowing when they perceive support from their supervisor (Rothwell and Baldwin 2007, Sims and Keenan 1998) or from their coworkers (Miceli et al. 2012, Umphress et al. 2003), low threat of retaliation (King 1999, Liyanarachchi and Newdick 2009), work place environment as less hostile and friendly climate (Rothwell and Baldwin 2007), and when citizens cooperate with authorities (Bergemann 2017). On the contrary, if individuals expect the retaliation to be strong, then they are less likely to engage in whistle-blowing (Liyanarachchi and Newdick 2009).

**Network positions and probability of whistle-blowing**

Even though contextual factors suggest that individuals need to perceive less retaliation from the focal actor who commits unethical behavior and to get potential supporters, it is not yet clear: first, who can receive this kind of information effectively and second, who can realize the possibility of whistle-blowing by leveraging their network positions. Research on social networks has shown that different network positions provide different resources and benefits. Depending on their network positions, individuals perceive the situation of whistle-blowing differently. For example, if individuals occupy high-network status positions (Bonacich and Lloyd 2001), they can access better/superior resources so they do not rely on the resources of the focal actor i.e., sexual harasser. Therefore, these individuals do not have to worry about severe retaliation from the sexual harasser. If individuals are closer to previous whistle-blowers, they can easily notice that some people have started whistle-blowing. Also, they can exchange information with each other more easily and quickly when they are not distant in a network of individuals. Moreover, if individuals occupy brokerage position, they can get access to different information (Burt 1992) and effectively spread their intentions and idea to others by leveraging their networks (González-Bailón and Wang 2016). Therefore, we explore how network positions can amplify the probability of whistle-blowing and timing of whistle-blowing from the cases of whistle-blowing of sexual harassments in Hollywood.

## BACKGROUND

### Harvey Weinstein and whistle-blowers

Before #MeToo in Hollywood, Harvey Weinstein was a powerful person in Hollywood and the most thanked person at the Oscars (the Academy Awards). He also had power over the media. If people made him angry, he could easily end their careers. Moreover, he himself tried to keep complaints quiet. He hired employees to collected information about people and his accusers. Hence, his whistle-blowers were terrified and even if people in Hollywood knew what was going on ("What we learned" 2019) they did not speak up. Seth McFarlane made a joke about Weinstein’s behavior by saying “Congratulations, you five ladies no longer have to pretend to be attracted to Harvey Weinstein” at the Oscar ceremony in 2013 (Dicker 2017). Individuals who want to achieve success in this industry should carefully consider what

Weinstein prefers. Rejecting his offer and advances can hurt their career. Kate Beckinsale, who is one of whistle-blowers to Harvey Weinstein, commented that she had tough time in her career because she rejected his demands (Guglielmi 2017). Especially if a person who is not well connected realized something wrong is going on, others in Hollywood did not believe the person or just ignored the voice.

From 5th October in 2017, movie actresses started accusing Harvey Weinstein of sexual harassment over 30 years. This behavior of accusing Weinstein rapidly spread in Hollywood. By 1st June 2018, more than 80 women accused Weinstein of sexual harassment (Moniuszko and Kelly 2018). After Weinstein was accused by many actresses, more women came forward and accused other famous and powerful men such as James Toback, Luis C.K., and Brett Ratner in the movie industry (Guynn and Cava 2017).

In Hollywood, people recognized this speaking up about Harvey Weinstein's sexual assault as whistle-blowing. During #MeToo, people in Hollywood often use Twitter to express their idea and comments about sexual harassment and Harvey Weinstein. Ms. Llewellyn Smith, a writer in the Times and The Sunday Times, considered Ms. Rose McGowan, an actress and the first whistle-blower to Weinstein, a brave whistle-blower. Ms. Smith tweeted "Her Hollywood whistleblowing is heroic and long overdue". Ashley Judd, an actress and among the first whistle-blowers to Weinstein, used a word "whistleblower" in her tweets when she talks about sexual harassment.

**Social network and Hollywood movie industry**

These research settings are appropriate to observe what happens in Hollywood and incidents of whistle-blowing about sexual harassment. First, social capital is important in the movie industry (Bechky 2006). In Hollywood, people typically work in project organizations. Project organizations are "organizations with open boundaries through which individuals can expand their social network by moving freely from project to project without facing the constraints typically encountered in more stable organizations" (Cattani & Ferriani, 2008: 829). After finishing one project, people working in Hollywood join a new project (Jones 1996). As each project in Hollywood needs creativity and efficient production routines (Levinthal and Madsen 2006), casting proper individuals in a project is particularly important in this setting. Moreover, people are willing to work with those who have been successful in the past since individual's talent is not transparent in creative industry (Rossman et al. 2010).

If movie actors are associated with unfavorable impression/images, e.g., blacklisted actors, others in the industry avoid associating with them (Pontikes et al. 2010). Also, producers who occupy highly central positions in networks comprising of professionals in Hollywood tend to favor candidates who themselves are highly embedded in the industry (Cattani et al. 2014). Having a tie with people who occupy highly central network positions in the industry enables actors and actresses to develop and succeed in their career and become Oscar winners or nominees. Thus, they may continue benefitting from even one such collaboration with an individual who occupies a highly central position in the network of Hollywood professionals. For instance, movie trailers frequently publicize that award-winning actresses and/or actors feature in the movie; in some cases, even if these individuals do not have a large role in that movie. This situation is appropriate for explaining the struggles of individuals who suffer from sexual harassment by a powerful person and may be forced to stay quiet. Second, we can observe connections among movie actors by referring to film credits. Movie actors often collaborate with each other to pursue efficient production process (Perretti and Negro 2007). By referring to movie credits, we can make a network of actresses, actors, directors, producers, and screen writers.

## Data of analysis

To observe who can be whistle-blowers, we include female whistle-blowers of Harvey Weinstein by 1st June 2018. Hence, in our regression sample, we have actresses and female whistle-blowers from Hollywood. This is because whistle-blowers to Harvey Weinstein's sexual harassment are mostly actresses.

IMDb provides the lists of movies in each year (https://datasets.imdbws.com/). We could also get access to all data such as movie titles, movie id, year, names of cast and crews for each movie, and person id (alphanumeric unique identifier of the name created by IMDb). We collected the data on all casts of the movie, marital status, birth year of casts, producers, directors, writers, Oscar winner and nominees, and roles from IMDb (https://www.imdb.com/).

***Network*.**

To create a network, we focused on all movies released in the U.S. from 2015 to 2017. Since the benefits of network positions are strongest in the current network and they do not persist over time (Soda et al. 2004). Therefore, we considered the affiliation data of movie projects from the last three years (before #MeToo in Hollywood) to build a network. Also, people in the movie industry are not necessarily credited every year. To solve this problem, we used three-year windows to create a network and calculate the network measures (Cattani and Ferriani 2008, Ferriani et al. 2009).

We collected all the information of casts from IMDb. We included 10 actors or actresses who appear in the film credit. In addition to these actors and actresses, we included director(s), writers, and main 20 producers including roles such as executive producer, producer, co-producer, line producer, and co-executive producer. Then, we created a one-mode network i.e., people by people from an affiliation network i.e., who works with whom in a movie.

***Whistle-blower***.

We identified whistle-blowers from the complete lists of accusers published by USA TODAY on June 1, 2018 (https://eu.usatoday.com/story/life/people/2017/10/27/weinstein-scandal-complete-list-accusers/804663001/). For each whistleblower, this article lists the name, occupation (e.g., actresses, assistant, or former employee), and descriptions of sexual harassment. Also, Asia Argento showed the complete lists of victims of Harvey Weinstein's sexual harassments on her Twitter page on October 28, 2017 (https://www.thewrap.com/asia-argento-tweets-list-of-harvey-weinstein-accusers/). This data includes the victim's name, the year of sexual harassment, and the details of sexual harassment.

**Variables.**

***Dependent variables***.

*Whistle-blower* is a dummy variable that equals 1 if the actress accused Harvey Weinstein by 1$^{st}$ June 2018. Otherwise, this variable equals 0.

*Early whistle-blower & Late whistle-blower.* For the early whistle-blower variable, we coded 1 if the actress became a whistle-blower within a week of accounts of the first whistle-blowers. For the late whistle-blower variable, we coded 1 if the actress becomes a whistle-blower a week after first whistle-blowers. For sensitivity test, we change the above threshold from a week to five days and ten days.

***Independent variables.***

***Network variables.***

We compute all network measures by using the networkx package in Python.

*Eigenvector centrality*. To measure network status, we use eigenvector centrality for the same network that we used to calculate structural holes with Python (Bonacich and Lloyd 2001). If a focal actor is connected with another actor who has more connections, the focal actor will be more central and powerful (Kilduff and Brass 2010).

*Geodesic distance between focal actress and previous whistle-blowers.* We calculate the mean of geodesic distances between the focal actress and previous whistle-blowers. If the focal actor does not engage in whistle-blowing, calculate the mean of distance between she and first whistle-blowers.

*Structural holes.* We measure structural holes by using the network including Harvey Weinstein's direct ties and indirect ties i.e., actors, actresses, and crews. We used the additive inverse of Burt's (1992) original constraints measurement for calculating structural holes (Soda et al. 2019). Burt's constraint measure captures the extent to which the focal actor's network lacks structural holes (Soda et al. 2019). This specification allows us to measure open and close network as two polar opposites (Carnabuci and Diószegi 2015). This variable varies between 0 and 1 i.e., if the value of constraints is close to 0, the actor has greater structural holes. We used one minus constraints to directly measure a focal actor's structural holes (Carnabuci and Diószegi 2015, Soda et al. 2019).

***Individual characteristics variables.***

*Age & Age square.* We include age of each actress (*Age*) in 2017. We also calculate the square of age (*Age*Age*) to test the hypothesis. Older actresses have established their career compared to younger actresses, so due to her power and prominence, she can be whistle-blower. However, older actresses are strongly embedded in the rules or norms in the field i.e., they are less flexible about the new perspective. Also, in Hollywood movie industry, older actresses face difficult time to find their job. For example, Susan Sarandon, the Oscar winning actress, acknowledges that women in Hollywood find it difficult to find a job since Hollywood favors young actresses

(Cate 2014, Silverstein and Cadenas 2013). To consider this effect, we include age and age square.

*Oscar Winner/Nominee*. This is a dummy variable. If an actress wins or nominates an Oscar, she is considered among the most successful and distinguished screen actresses and can expand her visibility and exposure (Levy 2003). Also, she occupies a central position in the network of the industry since peers in the industry regard her as a prominent actress (Cattani et al. 2014).

*Visibility.* We include *Twitter* followers to measure the visibility effect. If an actress has many Twitter followers, she can be influential when she tweets about her opinions and ideas as many people can check and share it. Thus, Twitter followers an important role to enhance visibility of social actors.

*Media Coverage.* We collect the number of articles of an actress in 2016 from Factiva. More media coverage can indicate how popular she is in the industry. Articles can increase because she has many jobs in the industry in addition to her personal stories. We control this because the actress who does not receive enough media coverage might have more motivation to engage in whistle-blowing to attract more attention.

***Control variables.***

*Multi role in movies*. Some actresses work as directors, producers, or writers in a movie. These actresses can get access to a variety of resources such as social capital, cultural capital, and material capital (Baker and Faulkner 1991). To control this, we create a dummy variable. In a movie, if an individual has worked as an actress and in other roles such as a director, producer, screenwriter, and/or others in her career, this variable equals 1. Otherwise, it equals 0.

*Marital status* (Lee et al. 2004). Marriage status can protect actresses from sexual harassment. For instance, Nicole Kidman revealed that being married to Tom Cruise could keep her from being a victim of sexual harassed (Farzan 2018). If an actress is married with someone as of 2017, we coded this variable as 1. Otherwise, we code it as 0.

*Dependency on sexual harassers*. If focal actress and sexual harassers often worked together in movies, she may depend on sexual harassers for resources and job opportunities since sexual harassers are powerful in the industry. To control for this, we calculate the ratio of the number of movies in which both worked together divided by the total number of total movies that she was credited.

*Number of females to direct ties*. If an actress is surrounded by other whistle-blowers or females, she may be comfortable with speaking up. To control these effects, we calculated the number of whistle-blowers who are directly connected to the actress and divided it by the number of her direct ties.

**Analytical approach**

In our sample, we just focus on his female whistle-blowers in the model. If we include the male accusers and alleged sexual harassers, these accusers might face more difficulty to engage in whistle-blowing since they may need to explain their sexual orientation. In addition to this, the number of cases between male sexual harassers and accusers is few. Therefore, our analysis includes actresses i.e., potential whistle-blowers and female whistle-blowers. Moreover, we excluded actresses who are under 18 and over 70 years of age in 2017 from the final sample of analysis to exclude child actresses and retired actresses.

Whistle-blowing occurs infrequently i.e., the number of whistle-blowers is about 1 percent of all females in our sample. In this case, using a regular logistic regression would lead to biased estimates. Therefore, we use a rare-events logistic analysis that can adjust the bias generated by rare-events and produce estimations (King and Zeng 2001). We use a Stata procedure developed by Tomz, King, and Zeng(2003).

## RESULTS

We draw network graphs using NodeXL. Figure 1 shows the network among male sexual harassers and actors, actresses and crew members. Light blue sphere represents Harvey Weinstein. Purple sphere represents other male sexual harassers. In our additional analysis, we have 10 sexual harassers including Harvey Weinstein. Green spheres represent whistle-blowers such as Ashley Judd, Kate Beckinsale, and Mira Sorvino. Pink spheres show other actresses while silver spheres show the rest. The lines connecting the spheres demonstrates that the two individuals worked together between 2015 and 2017. Figure 2 shows examples of networks of whistle-blowers.

--- Figure 1 & Figure 2 are about here---

Table 1 reports the descriptive statistics and correlation coefficients for the dependent, independent, and control variables. We computed the variance inflation factors (VIF) for all the independent variables in the models. All of them were less than 5.0, which is the conventional cutoff (Neter et al. 1990).

---Table 1 is about here---

Table 2 reports the results for the rare-event logistic regression analysis of whistle-blowers to Harvey Weinstein. Model 1 includes non-network variables. Middle-aged individuals have a higher probability of whistle-blowing. (*Age*: $p < .01$, $\beta = 0.6337$, *Age square*: $p < .01$, $\beta = -0.0066$). Also, individuals who are *Oscar Winner/Nominees* ($p < .01$, $\beta = 1.8241$) are more likely to engage in whistle-blowing. Individuals who are visible ($p < .01$, $\beta =$

0.0000000436) and more media coverage ($p$ < .01, $\beta$ = 0.00002), they will become whistle-blowers. Moreover, individuals who have more movies with Harvey Weinstein (*Dependency on sexual harassers*) will be whistle-blowers ($p$ < .01, $\beta$ = 7.9186).

In Models 2 and 3, we add the network variables. Model 2 shows that individuals who have high-status in a network are more likely to engage in whistle-blowing. The coefficient of the *Eigenvector Centrality* is significant ($p$ < .05) and positive ($\beta$ = 0.1767). Model 3 presents that individuals who are far from previous whistle-blowers are less likely to be whistle-blowers.

The marginal effect suggests that as one standard deviation increases in network status, the probability of whistle-blowing increases by 0.049 percentage points (8.56% increase from the sample mean) in Model 2. As one standard deviation increases in Geodesic distance between focal actress and previous whistle-blowers, the probability of whistle-blowing decreases by 0.2 percentage points (35% decrease from the sample mean).

---Table 2 is about here---

Table 3 presents the rare-event analysis results of individual and network variables on early/late whistle-blowing. Model 1 shows that individuals who are in open network will be early whistle-blowers ($p$ < .05, $\beta$ = 3.4945) and Model 2 shows those individuals will also be late whistle-blowers ($p$ < .05, $\beta$ = 3.0856). Models 3 and 4 present the results of occupying positions with high-status in a network and early/late whistle-blowing. In Model 3, coefficients of eigenvector centrality are not significant for early whistle-blower. In Model 4, we find that high status individuals will be late whistle-blowers ($p$ < .01, $\beta$ = 0.2570).

The marginal effect suggests that as one standard deviation increases in structural holes, the probability of early whistle-blowing increases by 0.07 percentage points (27% increase from the sample mean) in Model 1. As one standard deviation increases in network status, the probability of late whistle-blowing increases by 0.04 percentage points (15% decrease from the sample mean).

As sensitivity tests, we change the thresholds to categorize early/late whistleblowing from seven days to five days and ten days in Tables 4 and 5. Consistent to results of Table 3, in Table 4 we find that individuals are in an open network will be early ($p < .1$, $\beta = 2.6549$) in Model 1 and late whistle-blowers ($p < .05$, $\beta = 3.5414$) in Model 2. Table 5 shows that individuals are in an open network will be early whistle-blowers ($p < .05$, $\beta = 3.1743$) in Model 1. Consistent to Table 3, we find that high-status individuals will be late whistle-blowers in Model 4 in Table 4 ($p < .05$, $\beta = 0.3013$) and Table 5 ($p < .01$, $\beta = 0.2601$).

---Table 3, 4, and 5 are about here---

**Additional analysis**

***Network.***

We conducted additional analysis by including more male sexual harassers and their female whistle-blowers in addition to Harvey Weinstein and his ones. In this sample, 56 % of whistle-blowers engaged in whistle-blowing about Harvey Weinstein's sexual assaults. We used the same network as main analysis.

***Whistle-blower.***

We identified male sexual harassers and their female whistle-blowers from the lists of accusers from Vox on 9th January 2019 (https://www.vox.com/a/sexual-harassment-assault-allegations-list). For Harvey Weinstein case, we use the same source and data as the main analysis. This website lists up the alleged sexual harassers and their whistle-blowers. It refers to the articles of each sexual harasser and whistle-blower from several sources such as Variety, The New York times, the Hollywood reporter, the guardian, the Huffington Post, and USA today. Unlike

Harvey Weinstein case, more actresses keep themselves anonymous. Hence, we included only those actors who were accused by at least one actress who did not anonymously report it.

***Variables.*** We used the same variables as main analysis.

**Results of additional analysis**

Table 6 reports the results of the additional analysis. Similar to main results, we use rare-event analysis. Model 1 includes non-network variables. Consistent with main analysis, we found that *Age* ($p < .01$, $\beta = 0.3722$) and *Age square* ($p < .01$, $\beta = -0.0041$). Hence, middle-aged actresses are more likely to engage in whistle-blowing compared to older and younger actresses. Also, we found that Oscar Winner/Nominee will be whistle-blowers ($p < .01$, $\beta = 1.8706$). Moreover, we found that individuals who are more visible ( $p < .05$, $\beta = 0.0000000320$) and receive more media coverage ($p < .05$, $\beta = 0.0000151$) are more likely to engage in whistle-blowing. We also found that actresses who depend on sexual harassers are more likely to become whistle-blowers ($p < .01$, $\beta = 6.4799$). Model 2 includes Eigenvector Centrality. The coefficient of this variable is significant ($p < .01$) and positive ($\beta = 0.1964$). Hence, high-status individuals are more likely to be whistle-blowers. Model 3 shows that actresses who are far from previous whistle-blowers are less likely to engage in whistle-blowing ($p < .01$, $\beta = -1.6223$). Model 4 includes all variables. Results for network variables are consistent with those of Models 2 and 3.

---Table 6 is about here---

Table 7 represents the rare-event regression results for early/late whistle-blowers. Models 1 and 2 show the effects of structural holes on probability of becoming early whistle-blowers and late whistle-blowers, respectively. Model 1 shows that individuals who are in an open network are more likely to be early whistle-blowers ($p < .05$, $\beta = 2.8215$). Model 3 presents the effects of network status on probability of being an early whistle-blower while Model 4 shows those on becoming a late whistle-blower. From Model 4, we found that high-status individuals are more likely to be late whistle-blowers ($p < .01$, $\beta = 0.2451$).

We conduct sensitivity tests as well. Similar to Table 4 and Table 5, we use five days in Table 8 and ten days in Table 9 as thresholds rather than seven days. We find consistent results i.e., individuals who are in an open network will be early whistle-blowers in Model 1 from Table 8 ($p < .1$, $\beta = 2.6549$) and from Table 9 ($p < .05$, $\beta = 3.1743$). Also, we find that high-status individuals will be late whistle-blowers in Model 4 from Table 8 ($p < .01$, $\beta = 0.2785$) and from Table 9 ($p < .01$, $\beta = 0.2483$).

---Table 7, 8, and 9 are about here---

*Effects of individual characteristics on whistle-blowing.*

We interpret the results of the effects of individual characteristics on probability of whistle-blowing as follows. First, we find that middle-aged individuals are more likely to be whistle-blowers.  This can be because younger people may face more retaliation and others might ignore what young people report since their career is not yet established (Miceli and Near 1992). On the contrary, older people are too familiar with the norms, rules, and way of thinking in the industry. Hence, they can be more rigid how to behave in the field and less open to new perspectives (Cirillo et al. 2013). Also, as their retirement likely comes soon, they might not care for people in the community compared to younger people who likely have a longer career ahead.

Second, we find that individuals who have high social status i.e., Osar winner/nominee are more likely to engage in whistle-blowing. This is consistent with status studies, which argue that high-status individuals feel less constrained for deviant behavior (Phillips and Zuckerman

2001). In this context, whistle-blowing can be deviant and non-accepted behavior. It is reasonable to apply this explanation to this finding.

Finally, results show that individuals who have high visibility and receive media coverage are more likely to engage in whistle-blowing. In this study, we define highly visible individuals as larger number of twitter followers and more media coverage as larger number of news articles, respectively. Individuals with more twitter followers and media coverage can indicate that their job performance is higher. Whistle-blowing literature suggests that individuals with high job performance are more likely to be whistle-blowers (Vadera et al. 2009).

*Effects of network positions on probability and timing of whistle-blowing.*

We also try to explain the effects of network positions on probability of whistle-blowing. We find that individuals with high network status have a greater probability of whistle-blowing. We interpret that these individuals can get access to and control resources (Brass et al. 2004). They do not have to rely on others who engage in sexual harassment. Hence, they can engage in whistle-blowing.

Regarding geodesic distances, we argue that shorter distance enables individuals to reach out the previous whistle-blowers and realize the possibility of whistle-blowing. In Hollywood context, Harvey Weinstein is so powerful and can break someone's career easily if individuals speak up about his unethical behavior. Individuals may not realize that whistle-blowing itself is possible in the industry. Hence, it is crucial for potential whistle-blowers to notice that someone has already spoken up. Also, the probability of information flow about this behavior can be higher (Singh 2005) if the distance between individuals and previous whistle-blowers is shorter.

We also examine how network positions can influence the timing of whistle-blowing. We find that individuals who are in an open network will be early whistle-blowers and individuals who are high social status will be late whistle-blowers. The explanation can be that individuals who are in an open network can spread information broadly and effectively (González-Bailón and Wang 2016). By doing so, these individuals can prepare for retaliation from an individual who engages in unethical behavior by creating more negative publicity for the individual. Also, compared to individuals who are in a closed network, individuals who are in an open network can realize the possibility of whistle-blowing in early timing. This is because they are connected to different people/communities and thus have information advantage (Burt 1992, 2004). Therefore, open networks enable individuals to engage in whistle-blowing in early timing.

We also try to understand why individuals who are high network status will be late whistle-blowers. One potential explanation is these individuals do not want to be the first whistle-blowers and last ones. In early timing, they can use the “wait and see” attitude to whistle-blowing. Even high-status individuals can get sanctions if the behavior is not accepted in the industry (Pontikes et al. 2010). Also, network status is an indicator of popularity (Bonacich and Lloyd 2001). If others think whistle-blowing as unacceptable, network status of whistle-blowers can decrease. Hence, they do not want to be early whistle-blowers. However, as more people engage in whistle-blowing, if individuals with high-network status do not engage in whistle-blowing even though they should do so, others might consider them incompetent. High network status individuals are considered as competent (Darley and Gross 1983, Humphrey 1985). To maintain this impression, high-network status individuals will be late whistle-blowers.

## CONCLUSIONS AND POTENTIAL CONTRIBUTIONS

This study explores who can be whistle-blowers from the social network perspective and when individuals engage in whistle-blowing by focusing on the incidents of whistle-blowing of sexual harassment by Harvey Weinstein and others in 2017. By conducting this study, we provide several contributions to the literature.

First, this study is among the first to link and investigate network positions and whistle-blowing. Whistle-blowing can be a risky behavior for individuals (Vadera et al. 2013); if they engage in whistle-blowing, they may receive penalty from the target of whistle-blowing or members of the community. While co-worker's support matters for individuals to engage in whistle-blowing (Robinson and Kraatz 1998) and to avoid further retaliation after whistle-blowing (Rehg et al. 2008), it is not clear who can receive/perceive better information and supports from others. Depending on network positions, individuals receive more information and perceive more opportunities to engage in whistle-blowing. Also, it is crucial for whistle-blowers to collect information before engaging in whistle-blowing because whistle-blowing is costly. By connecting network literature with whistle-blowing literature, we can consider and demonstrate this.

Second, this study tries to capture the diffusion of whistle-blowing. We find that different network positions can determine early or late whistle-blowing. Diffusion literature explains that social actors have different intensions to adopt new practices depending on the timing of adoption (e.g.,Tolbert & Zucker, 1983). It is worth observing how network positions enable individuals to perceive the opportunities of whistle-blowing and engage in whistle-blowing.

Finally, social network research has examined how network structure affects final outcomes such as better job performance, effectiveness of job search (Brass 2011), and creativity (Borgatti and Halgin 2011). Whistle-blowing is also one of final outcomes; however, compared to job performance or creativity, whistle-blowing is challenging. This is because, after engaging in whistle-blowing, individuals may face severe punishment or retaliation by others. For example, whistle-blowing may destroy their career; whistle-blowers may not be able to go back to the previous status-quo. Hence, it is worth observing how individuals who occupy certain network positions engage in whistle-blowing.

## LIMITATIONS AND EXTENSIONS

There are several limitations and extensions in this study. First, this study examines the diffusion of whistle-blowing among actresses by considering early and late whistle-blowers. We assume that each whistle-blower can observe others and decide to engage in whistle-blowing by referring to the timeline of news article and sources. However, the accusing behavior to alleged sexual harassers spreads very quickly. There are possibilities that this assumption is not accurate. Also, in this case whistle-blowing behavior is a rare-event and is over in a relatively short time. Thus, we cannot categorize the timing of whistle-blowers in a more fine-grained way and must use early/late whistle-blowers as dependent variables.

Second, our network is an affiliation network. Affiliation networks represent who works with whom in a movie. This network cannot capture friendship or informal networks. For example, if we can get access to data on agents of actresses or participations in film festivals, we might capture informal network. This is because people in this industry can meet others through these events or agents.

Third, we have limitations of data for our dependent variable. We do not question if sexual harassment actually occurred between whistle-blowers and alleged sexual harassers. We do not deny that there is possibility that whistle-blowers may accuse an individual of sexual harassment even if the individual did not actually commit any harassments i.e., false accusation. However, some studies argue that individuals are less likely to share fake news on their social media pages such as Facebook (Guess et al. 2019). Whistle-blowing itself can be risky behavior because whistle-blowers can lose their jobs or alleged sexual harassers might severely retaliate to whistle-blowers. Hence, we assume that this possibility that accusers falsely report sexual harassment is not so high in our study. Also, our dependent variable can include individuals who face sexual harassments and do not speak up or stay anonymous. These problems lead to limitations of our data.

Fourth, in our empirical strategy, there is an assumption that actresses in our sample are potentially targets of sexual harassments by Harvey Weinstein and others. This might not be true. It can be some individual characteristics can improve the sample selection. However, currently this is a limitation of our empirical strategy. Finally, this study focuses on Hollywood movie industry, so we may face generalization problems. However, we could observe whistle-blowers not only in entertainment industry but also politics and business fields. The characteristics of industry can vary, but we can examine the similar questions in different industries in the future. Despite these limitations, we believe that this study has contributions to social network research as well as whistle-blowing research.

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**Figure 1.** Network of alleged sexual harassers and female whistle-blowers

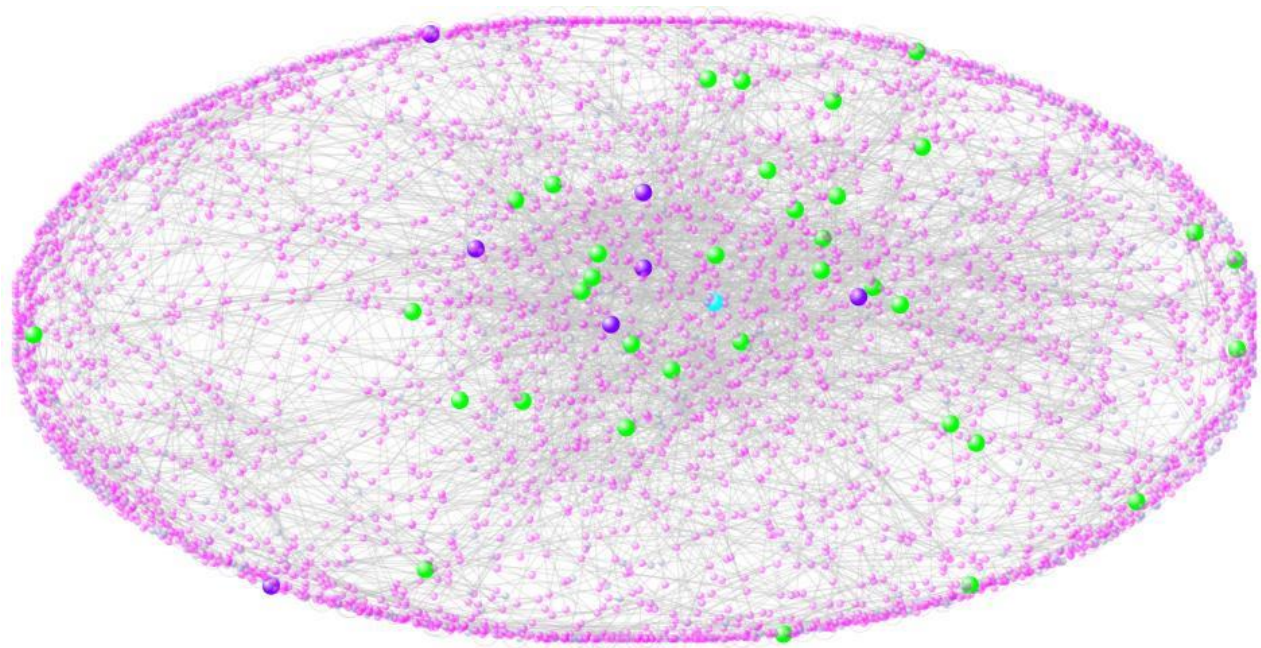

**Figure 2.** Examples of network plot of actresses (Ashley Judd, Sienna Miller, Gwyneth Paltrow, and Rose McGowan)

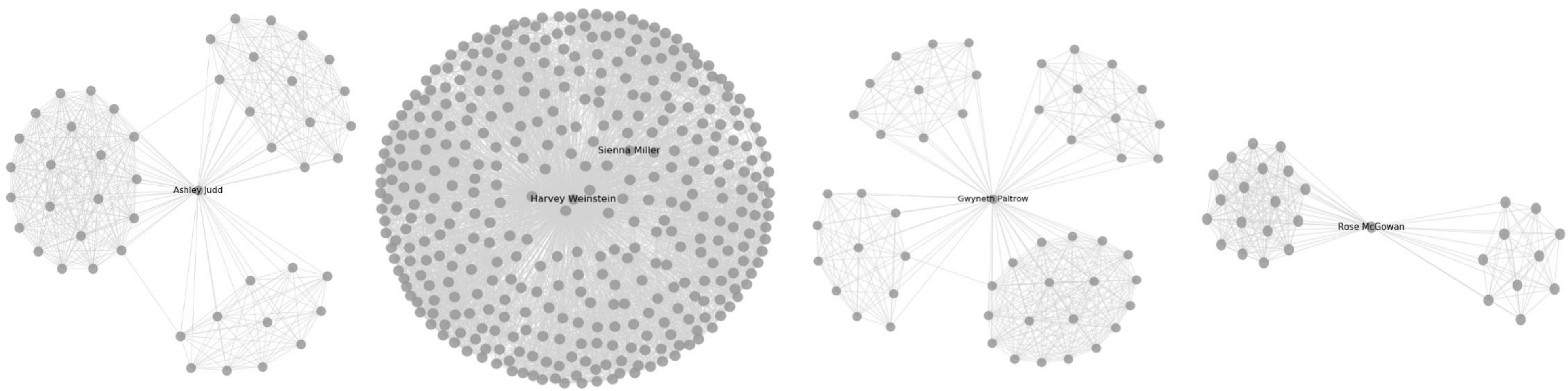


**Table 1.** Descriptive Statistics and Correlations

| Variables | Mean | S.D. | 1) | 2) | 3) | 4) | 5) | 6) | 7) | 8) | 9) | 10) | 11) | 12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1) Whistle-blowers | .006 | .075 | 1 | | | | | | | | | | | |
| 2) Eigenvector Centrality | .005 | 1.011 | 0.07 | 1 | | | | | | | | | | |
| 3) Geodesic distance | 3.573 | .707 | -0.10 | -0.18 | 1 | | | | | | | | | |
| 4) Structural holes | .548 | .375 | 0.06 | 0.23 | -0.32 | 1 | | | | | | | | |
| 5) Oscar Winner/Nominee | .025 | .155 | 0.09 | 0.23 | -0.20 | 0.12 | 1 | | | | | | | |
| 6) Multi roles | .624 | .484 | 0.03 | 0.09 | -0.24 | 0.11 | 0.12 | 1 | | | | | | |
| 7) Marital status | .249 | .432 | 0.03 | 0.05 | -0.11 | 0.03 | 0.10 | 0.13 | 1 | | | | | |
| 8) Age | 39.598 | 12.178 | 0.04 | -0.03 | -0.05 | -0.02 | 0.14 | 0.14 | 0.23 | 1 | | | | |
| 9) Age square | 1716.281 | 1062.527 | 0.03 | -0.03 | -0.04 | -0.02 | 0.15 | 0.12 | 0.20 | 0.99 | 1 | | | |
| 10) Dependency on sexual harassers | .003 | .026 | 0.06 | 0.06 | -0.13 | 0.07 | 0.07 | 0.06 | 0.02 | -0.01 | -0.02 | 1 | | |
| 11) Visibility | 122000 | 2020000 | 0.01 | 0.00 | -0.02 | 0.03 | -0.01 | 0.03 | 0.01 | -0.02 | -0.02 | -0.01 | 1 | |
| 12) Media Coverage | 287.807 | 4717.878 | 0.02 | 0.04 | -0.05 | 0.04 | 0.06 | 0.04 | 0.04 | 0.04 | 0.05 | 0.02 | 0.29 | 1 |

**Table 2.** Regression results of rare-event analysis for whistle-blowers to Harvey Weinstein

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Eigenvector Centrality | | 0.1767** | | 0.1429* |
| | | (0.0810) | | (0.0827) |
| Geodesic distance between focal actress and previous whistle-blowers | | | -2.0356*** | -1.9948*** |
| | | | (0.4133) | (0.4042) |
| Age | 0.6337*** | 0.6299*** | 0.5699*** | 0.5765*** |
| | (0.2260) | (0.2220) | (0.2157) | (0.2183) |
| Age square | -0.0066*** | -0.0065*** | -0.0059** | -0.0059** |
| | (0.0024) | (0.0024) | (0.0023) | (0.0024) |
| Oscar Winner/Nominee | 1.8241*** | 1.4736** | 0.9715* | 0.6826 |
| | (0.5338) | (0.5883) | (0.5431) | (0.5936) |
| Visibility | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Media coverage | 0.0000** | 0.0000** | 0.0000** | 0.0000** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Multi roles | 0.4627 | 0.4439 | -0.1659 | -0.1655 |
| | (0.5440) | (0.5448) | (0.5584) | (0.5580) |
| Marital status | 0.0148 | -0.0868 | 0.0916 | 0.0009 |
| | (0.4280) | (0.4411) | (0.4361) | (0.4461) |
| Dependency on sexual harassers | 7.9186*** | 7.6483*** | 6.8429*** | 6.5270** |
| | (2.4377) | (2.5465) | (2.6005) | (2.7349) |
| Number of females in direct ties | 0.0697 | 0.0581 | 0.0079 | 0.0024 |
| | (0.0768) | (0.0750) | (0.0828) | (0.0825) |
| Constant | -20.2310*** | -20.1714*** | -11.7784** | -12.1133** |
| | (5.1228) | (5.0225) | (5.0575) | (5.0906) |
| Observations | 4243 | 4243 | 4221 | 4221 |
| Log likelihood | -84.7028 | -80.6444 | -66.1171 | -62.6190 |
| Chi-squared | 49.5405 | 54.4891 | 60.3092 | 64.8690 |

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 3.** Regression results of rare-event analysis of early/late whistle-blowers to Harvey Weinstein

| | Model 1<br>early whistle-blower | Model 2<br>late whistle-blower | Model 3<br>early whistle-blower | Model 4<br>late whistle-blower |
|---|---|---|---|---|
| Structural holes | 3.4945** | 3.0856** | | |
| | (1.6988) | (1.5587) | | |
| Eigenvector Centrality | | | 0.0543 | 0.2570*** |
| | | | (0.1226) | (0.0898) |
| Age | 0.6114** | 0.4836* | 0.5939* | 0.4583* |
| | (0.3075) | (0.2651) | (0.3217) | (0.2625) |
| Age square | -0.0063* | -0.0047* | -0.0062* | -0.0044 |
| | (0.0033) | (0.0028) | (0.0035) | (0.0028) |
| Oscar Winner/Nominee | 1.3174* | 1.1533 | 1.9582*** | 1.0038 |
| | (0.6887) | (0.7956) | (0.7192) | (0.8953) |
| Visibility | 0.0000** | 0.0000*** | 0.0000*** | 0.0000*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Media Coverage | 0.0000* | 0.0000 | 0.0000** | 0.0000* |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Multi roles | 2.0818 | -0.6496 | 2.2821 | -0.5210 |
| | (1.4578) | (0.6321) | (1.4553) | (0.6333) |
| Marital status | 0.1280 | -0.0151 | 0.0791 | -0.2075 |
| | (0.5773) | (0.5973) | (0.5878) | (0.6311) |
| Dependency on sexual harassers | 8.5383*** | 8.8068*** | 8.4384*** | 8.0649** |
| | (3.1091) | (3.2258) | (2.9065) | (3.2089) |
| Number of females in direct ties | -0.2051 | 0.0937 | -0.1469 | 0.1334 |
| | (0.1421) | (0.0960) | (0.1423) | (0.0920) |
| Constant | -23.6194*** | -19.4738*** | -20.8524*** | -16.9207*** |
| | (7.2234) | (6.2087) | (7.3569) | (5.9742) |
| Observations | 4243 | 4243 | 4243 | 4243 |
| Log likelihood | -22.3593 | -28.6681 | -24.3530 | -27.2043 |
| Chi-squared | 36.1784 | 30.0643 | 40.5599 | 42.9475 |

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 4.** Regression results of early and late whistle-blowers to Harvey Weinstein (5 days)

| early whistle-blowers < 6 days<br>late whistle-blowers >= 6 days | Model 1<br>early whistle-blower | Model 2<br>late whistle-blower | Model 3<br>early whistle-blower | Model 4<br>late whistle-blower |
|---|---|---|---|---|
| Structural holes | 2.6549* | 3.5414** | | |
| | (1.5998) | (1.6355) | | |
| Eigenvector Centrality | | | -0.1279 | 0.3013*** |
| | | | (0.2358) | (0.0821) |
| Constant | -19.3204*** | -21.4918*** | -17.6895** | -18.6006*** |
| | (7.1674) | (6.5644) | (7.0273) | (6.4561) |
| Control variables | Included | Included | Included | Included |
| Observations | 4243 | 4243 | 4243 | 4243 |
| Log likelihood | -14.6460 | -33.0249 | -14.6749 | -30.6207 |
| Chi-squared | 36.9341 | 29.1317 | 41.4716 | 46.7467 |

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 5.** Regression results of early and late whistle-blowers to Harvey Weinstein (10 days)

| early whistle-blowers <11 days<br>late whistle-blowers >= 11 days | Model 1<br>early whistle-blower | Model 2<br>late whistle-blower | Model 3<br>early whistle-blower | Model 4<br>late whistle-blower |
|---|---|---|---|---|
| Structural holes | 3.1743** | 3.1132 | | |
| | (1.3620) | (2.1489) | | |
| Eigenvector Centrality | | | 0.0600 | 0.2601*** |
| | | | (0.1235) | (0.0950) |
| Constant | -23.1848*** | -16.6004** | -20.8710*** | -13.4134** |
| | (7.1459) | (6.6984) | (6.7831) | (5.9965) |
| Control variables | Included | Included | Included | Included |
| Observations | 4243 | 4243 | 4243 | 4243 |
| Log likelihood | -39.7372 | -7.1176 | -42.5144 | -4.0787 |
| Chi-squared | 37.3284 | 31.6872 | 40.7976 | 46.7643 |

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 6.** Regression results of additional analysis for whistle-blowers to all sexual harassers

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Eigenvector Centrality | | $0.1964^{***}$ | | $0.1667^{***}$ |
| | | (0.0632) | | (0.0644) |
| Geodesic distance between focal actress and previous whistle-blowers | | | $-1.6223^{***}$ | $-1.5790^{***}$ |
| | | | (0.2997) | (0.2961) |
| Age | $0.3722^{***}$ | $0.3835^{***}$ | $0.3479^{**}$ | $0.3579^{***}$ |
| | (0.1374) | (0.1391) | (0.1360) | (0.1379) |
| Age square | $-0.0041^{***}$ | $-0.0042^{***}$ | $-0.0038^{**}$ | $-0.0038^{**}$ |
| | (0.0015) | (0.0016) | (0.0015) | (0.0016) |
| Oscar Winner/Nominee | $1.8706^{***}$ | $1.3974^{***}$ | $1.0689^{**}$ | 0.6835 |
| | (0.4509) | (0.5078) | (0.4583) | (0.5072) |
| Visibility | $0.0000^{**}$ | $0.0000^{**}$ | $0.0000^{*}$ | $0.0000^{**}$ |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Media coverage | $0.0000^{**}$ | $0.0000^{**}$ | $0.0000^{**}$ | $0.0000^{*}$ |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Multi roles | $0.9385^{**}$ | $0.9013^{*}$ | 0.4755 | 0.4509 |
| | (0.4742) | (0.4751) | (0.4828) | (0.4833) |
| Marital status | 0.0937 | -0.0077 | 0.0975 | 0.0087 |
| | (0.3476) | (0.3563) | (0.3491) | (0.3560) |
| Dependency on sexual harassers | $6.4799^{***}$ | $6.1948^{**}$ | $5.2173^{**}$ | $4.8602^{*}$ |
| | (2.3517) | (2.4913) | (2.4904) | (2.6625) |
| Number of females in direct ties | -0.0029 | -0.0137 | -0.0695 | -0.0754 |
| | (0.0682) | (0.0669) | (0.0723) | (0.0718) |
| Constant | $-13.4541^{***}$ | $-13.7600^{***}$ | $-7.1768^{**}$ | $-7.6158^{**}$ |
| | (2.9607) | (3.0026) | (3.1013) | (3.1495) |
| Observations | 4243 | 4243 | 4221 | 4221 |
| Log likelihood | -150.8602 | -144.7220 | -132.7164 | -127.5782 |
| Chi-squared | 54.9836 | 64.4161 | 72.2787 | 80.6581 |

Standard errors in parentheses, $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 7.** Regression results of additional analysis for early/late whistle-blowers to all sexual harassers

| | Model 1<br>early whistle-blower | Model 2<br>late whistle-blower | Model 3<br>early whistle-blower | Model 4<br>late whistle-blower |
|---|---|---|---|---|
| Structural holes | 2.8215** | 0.9354 | | |
| | (1.3666) | (0.6763) | | |
| Eigenvector Centrality | | | 0.0544 | 0.2451*** |
| | | | (0.1233) | (0.0665) |
| Age | 0.6739** | 0.2498* | 0.6615* | 0.2584* |
| | (0.3271) | (0.1450) | (0.3405) | (0.1477) |
| Age square | -0.0070** | -0.0027* | -0.0070* | -0.0027* |
| | (0.0036) | (0.0016) | (0.0037) | (0.0017) |
| Oscar Winner/Nominee | 1.4089** | 1.5051*** | 1.9605*** | 1.0149 |
| | (0.6832) | (0.5804) | (0.7146) | (0.6630) |
| Visibility | 0.0000** | 0.0000* | 0.0000*** | 0.0000** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Media coverage | 0.0000* | 0.0000* | 0.0000** | 0.0000* |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Multi roles | 1.0084 | 0.6989 | 1.1836 | 0.6923 |
| | (0.8893) | (0.5370) | (0.8852) | (0.5374) |
| Marital status | 0.0280 | -0.0440 | -0.0139 | -0.1866 |
| | (0.5639) | (0.4352) | (0.5742) | (0.4518) |
| Dependency on sexual harassers | 8.3974*** | 5.8142* | 8.4502*** | 5.5278* |
| | (3.0662) | (2.9828) | (2.9102) | (3.2218) |
| Number of females in direct ties | -0.1829 | 0.0064 | -0.1266 | 0.0180 |
| | (0.1348) | (0.0804) | (0.1348) | (0.0769) |
| Constant | -23.3390*** | -11.6016*** | -21.2421*** | -11.3881*** |
| | (7.4566) | (3.1267) | (7.6514) | (3.1562) |
| Observations | 4243 | 4243 | 4243 | 4243 |
| Log likelihood | -29.5064 | -98.0715 | -31.0199 | -92.5352 |
| Chi-squared | 38.4262 | 34.9355 | 41.8169 | 52.0852 |

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 8.** Regression results of early and late whistle-blowers to all sexual harassers (5 days)

| early whistle-blowers < 6 days<br>late whistle-blowers >= 6 days | Model 1<br>early whistle-blower | Model 2<br>late whistle-blower | Model 3<br>early whistle-blower | Model 4<br>late whistle-blower |
|---|---|---|---|---|
| Structural holes | 2.6549$^{*}$ | 1.0166 | | |
| | (1.5998) | (0.6612) | | |
| Eigenvector Centrality | | | -0.1279 | 0.2785$^{***}$ |
| | | | (0.2358) | (0.0644) |
| Constant | -19.3204$^{***}$ | -12.2786$^{***}$ | -17.6895$^{**}$ | -12.0979$^{***}$ |
| | (7.1674) | (3.2392) | (7.0273) | (3.2905) |
| Controls | Included | Included | Included | Included |
| Observations | 4243 | 4243 | 4243 | 4243 |
| Log likelihood | -14.6460 | -102.8343 | -14.6749 | -95.6032 |
| Chi-squared | 36.9341 | 35.0856 | 41.4716 | 56.9719 |

Standard errors in parentheses, $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 9.** Regression results of early and late whistle-blowers to all sexual harassers (10 days)

| early whistle-blowers <11 days<br>late whistle-blowers >= 11 days | Model 1<br>early whistle-blower | Model 2<br>late whistle-blower | Model 3<br>early whistle-blower | Model 4<br>late whistle-blower |
|---|---|---|---|---|
| Structural holes | 3.1743$^{**}$ | 0.5078 | | |
| | (1.3620) | (0.6964) | | |
| Eigenvector Centrality | | | 0.0600 | 0.2483$^{***}$ |
| | | | (0.1235) | (0.0692) |
| Constant | -23.1848$^{***}$ | -10.0219$^{***}$ | -20.8710$^{***}$ | -10.0092$^{***}$ |
| | (7.1459) | (3.1742) | (6.7831) | (3.2212) |
| Controls | Included | Included | Included | Included |
| Observations | 4243 | 4243 | 4243 | 4243 |
| Log likelihood | -39.7372 | -78.6271 | -42.5144 | -72.3084 |
| Chi-squared | 37.3284 | 36.7127 | 40.7976 | 54.8540 |

Standard errors in parentheses, $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Before shooting star fade out: Formation of status heterophilous ties by high-status actors**

## ABSTRACT

Per literature on status homophily, social actors work with those with a similar status as theirs. High status actors refrain from working with a low-status actor to avoid perceptions of low quality of their product especially under high uncertainty about their products. However, status heterophily research reports collaborations among actors who differ in their social status. High-status actors receive extraordinary amount of recognition. We examine if high-status actors form status heterophilous ties when they need to share recognition with their partners. To avoid competing with high-status partners for recognition, we expect that high-status actors prefer to work with low-status actors. We also consider three situations that can increase the formation of status heterophilous ties: awareness to a product, more information about a product from critics and age of high-status actors. We use difference-in-differences analysis to test our hypotheses by collecting data on Oscar winner directors and nominees as counterfactuals.

Keywords: Status, Status heterophilous ties, Recognition, Hollywood

## INTRODUCTION

Audiences and consumers infer quality of a product from the status of its producer when they cannot determine its quality until they actually experience it (Podolny, 1993, 1994). Status is a focal actor's position in a social hierarchy that other actors may rely on while assessing the focal actor's products relative to that of other actors (Podolny, 2010). This reliance gets stronger as the uncertainty about the product increases (Podolny, 1994). Hence, status plays a crucial role in signaling the level of quality of a product to audiences who typically control access to important resources.

Status of social actors is determined by their affiliations (Jensen, 2006; Podolny & Phillips, 1996; Washington & Zajac, 2005). Literature on status homophily explains that high-status actors work with other high-status actors (Dahlander & McFarland, 2013; McPherson & Smith-Lovin, 1987; Podolny, 1994; Podolny & Phillips, 1996). This is because in a collaboration between a high-status actor and a low-status actor audiences may perceive the product as low-status (Benjamin & Podolny, 1999). To avoid this negative status transfer, social actors prefer to work with partners who have same status as theirs (Podolny, 1993). However, recent studies have found boundary conditions to status-homophily by demonstrating certain conditions in which high-status actors collaborate with low-status actors (Castellucci & Ertug, 2010; Shipilov, Li, & Greve, 2011). These studies suggest that affiliations among high-status actors and low-status actors happen when high-status actors expect more benefits than costs from working with low-status partners. For example, high-status actors work with low-status partners when they can extract more effort from their low-status partners (Castellucci & Ertug, 2010) and they can garner tribute and information from low-status partners (Shipilov et al., 2011). However, this stream of research has not yet considered the situation and mechanism in which recognition i.e., a public judgement about the quality of the recipient's work (Heinich, 2009) becomes more important to a high-status actor.

High-status provides benefits, resources, and opportunities to social actors e.g., increased recognition for a given level of quality (Azoulay, Stuart, & Wang, 2013; Kovács & Sharkey, 2014; Merton, 1968; Sharkey & Kovács, 2018; Simcoe & Waguespack, 2011). Some benefits such as recognition from audiences are not equally allocated among high-status actors (Merton, 1968). When high-status actors work with high-status partners, they must share the limelight with their partners rather than claim all the recognition from audiences. In other words, in a collaboration among high-status actors, audiences cannot identify who contributes more to the product and they may think that each high-status actor equally worked on it. To avoid this situation, we expect that high-status social actors work with low-status partners. By working with low-status partners, they can push their style and idea in their following products and clearly show that they are the main contributors. We also consider three situations that can positively moderate the selection of lower-status partners by a high-status actor: awareness to products of an actor (Lampel & Shamsie, 2000), information critics' evaluation of the product (Eliashberg & Shugan, 1997; Janssen, 1997), and an actor's age (Serfling, 2014).

We test our hypotheses by conducting a difference-in-differences analysis on a sample of professionals working in the Hollywood film industry. We collect and compare data on movies made by an Oscar winner (high-status) or Oscar-nominated director (counterfactual) between 1939 and 2020. This setting is appropriate to observe how high-status actors decide on the status of partners as Oscar winners and nominees are not so different in terms of their skills and quality. Since the film industry is a creative industry, recognition is crucial since winning an Oscar is relatively unexpected and rare, and careers in it are unstable compared to those in scientific fields (Heinich, 2009). Also, winning Oscar may not necessarily assure the success of following products. Results support our hypotheses that high-status social actors work with lower-status partners. We also find that this relationship is stronger when awareness to the product increases, critics provide evaluations to the product, and high-status social actors are older. Our study advances the literature on status heterophily (Castellucci & Ertug, 2010; Shipilov et al., 2011) by introducing a new mechanism to explain why social actors work with low-status partners. To do so, we argue that high-status social actors prefer to receive all recognition themselves rather than sharing it with other high-status actors.

## THEORY

### Status and homophilous tie formation

Status is a focal actor's position in a social hierarchy that other actors may rely on while assessing the focal actor's products relative to that of other actors' (Podolny, 2010). Status is closely linked with deference (Podolny & Phillips, 1996). Social actors defer to high-status actors and acknowledge that they are superior to them (Blau, 2017; Podolny & Phillips, 1996). When audience cannot observe the quality of a product until they actually experience it, they infer quality of the product from the status of its producers (Podolny, 1993, 1994).

After becoming high-status, social actors garner extraordinary recognition (Azoulay et al., 2013; Merton, 1968). Recognition is defined as a public judgement about the quality of the recipient's work (Heinich, 2009). For a given level of quality, high-status actors receive greater recognition and attention than low-status actors. High-status actors typically have first choice in selecting exchange partners, resource providers, and collaborators.

High-status social actors tend to form a tie with high-status partners i.e., status homophily (Podolny, 1993, 1994). They do so because status of an actor is in part determined by affiliations (Piazza & Castellucci, 2014; Podolny, 1993; Washington & Zajac, 2005). In other words, when high-status actors affiliate with lower status partners, high-status actors might lose (some of) their status (Piazza & Castellucci, 2014; Podolny, 1993). By affiliating with other high-status actors, high-status actors can signal to audiences that they are high-status.

For example, in the wine-industry high-status firms enter in relationships with other high-status firms (Benjamin & Podolny, 1999). Therefore, high-status actors form an exclusive club that can be accessed only by high-status actors. By being in this elite club, they get considerably more recognition than their peers who are equally good but not in the elite club. Indeed, this has been demonstrated by the phenomenon of the 41st chair (Merton, 1968). Especially when uncertainty of the transaction increases, this tendency becomes stronger (Podolny, 1994).

### Recognition and heterophilous tie formation

While affiliating with a high-status actor has benefits for high-status actors, high-status actors may not necessarily want to share these benefits with their high-status partners. Some benefits such as recognition from audiences are not equally allocated among high-status actors (Merton, 1968). When they exhibit status homophily, high-status actors need to share the recognition for their work with their high-status collaborators. In this case, audiences may not be able to equally give high recognition to the efforts of all these contributors. For example, in case of a publication, if a high-status author publishes a paper with other high-status authors, the credit of the paper is divided by all authors rather than one author[1] (Bikard, Murray, & Gans, 2015; Price, 1981). Hence, a high-status author might not enjoy this situation because this author wants to get all recognitions from audience. Once high-status actors receive extraordinary recognition, they prefer to take all recognition themselves. This can be because becoming high-status is very costly. Also, this competition for recognition among high-status can decrease team performance (Groysberg, Polzer, & Elfenbein, 2011). Especially when individuals face instability within the hierarchy of a team, they pursue self-interest rather than a group goal by

[1] This study considers the situation that social actors need to form a team due to complexity of work rather than they work alone. In publications fields, it is possible for individuals work alone but in a movie industry, individuals work with others as a team.

excluding a proficient and highly skilled group member (Maner & Mead, 2010). Hence, we can argue that high-status actors may prefer to work with low-status actors to avoid the situation that high-status actors may have to share recognition with other high-status partners and thus receive less recognition than they generally would.

While affiliations with lower status partners can cause high-status actors to lose their status (Piazza & Castellucci, 2014; Podolny, 1993; Washington & Zajac, 2005), i.e., the quality of high-status actors might be perceived as low, studies have shown that high-status actors not always form ties with high-status partners. Status heterophily may have benefits for a high-status actor. High-status actors work with low-status actors as they can extract greater effort from low-status actors (Castellucci & Ertug, 2010). From the social network perspective, high-status actors in brokerage positions, i.e., brokers, are more likely to initiate a tie with low-status ones (Shipilov et al., 2011). This is because high-status brokers recognize that low-status partners give tributes to them and select low-status partners. By doing so, they avoid collaborative negotiation about the partnership and push their views on their low-status partners. These studies suggest that high-status actors initiate ties with low-status partners as heterophilous ties provide advantages to high-status actors.

If high-status actors work with low-status partners, they can continue getting greater recognition for their work. Moreover, high-status actors do not have to share the limelight with other high-status actors and thus may not be evaluated relative to other high-status actors. While low-status actors may benefit in their status from this affiliation, high-status actors can impose their styles and preferences on low-status actors, so the audiences associate the outcome of this collaboration more to the high-status actor. Thus, high-status actors can receive recognition from their audiences and not share it with others. Therefore:

*Hypothesis 1: High-status social actors will work with low-status partners.*

In Hypothesis 1, we argue that high-status actors work with low-status partners to receive most of the recognition from their audiences. If high-status actors work with other high-status actors, then would have to proportionately share recognition from their audience with their high-status collaborators. In Hypothesis 2, we consider the situation that audiences' awareness to a product increase. When ease of accessing information about a product increases, audiences can easily get more detailed information about various aspects and components of that product i.e., audiences' awareness to the product increase (Lampel & Shamsie, 2000; Ratchford, Lee, & Talukdar, 2003). Hence, audiences can more easily find and possibly evaluate the products of a focal actor and make more informed decisions when giving recognition to a social actor for the actors' products.

For example, audiences can get information about actors who have collaborated to develop a product and thus infer if these collaborators are high-status. If most of the collaborators are high-status, audiences may think that the product has been developed by a team of high-status actors rather than a single high-status actor. In this case, high-status actors must share among themselves the recognition that their product receives from their audiences. Since all the team members are high-status and they may have to compete with each other to get additional recognition/attention from their audiences. On the other hand, if a focal actor is high-status but other collaborators are low-status, then the focal actor can appropriate a lion's share of the audiences' recognition with the low-status collaborators. Low-status collaborators are likely content with this arrangement as they can improve their status by affiliating with a high-status actor.

To sum up, when search costs decrease and audiences can easily access information about a focal actor's product and its contributors, focal actors increasingly worry about sharing their audience's recognition with their collaborators for that product. Therefore:

*Hypothesis 2: After audiences get access to information on partners more easily, high-status social actors will work with low-status partners.*

As previously mentioned, increasing awareness to a focal actor's products by audiences (Lampel & Shamsie, 2000) is an important consideration for high-status actors when making decisions on their collaborators. Another dimension of information about a product can be if third-party critics evaluate it (Basuroy, Chatterjee, & Ravid, 2003; Hsu, 2006). While evaluating products, audiences rely on third-party critics when evaluating numerous products in the marketplace. If a product is reviewed by critics, then audiences consider it to have legitimacy and thus evaluate it (Eliashberg & Shugan, 1997; Janssen, 1997); whereas audiences ignore products that critics have not reviewed. When audiences can easily figure out if and how critics have reviewed a product, they can quickly decide to evaluate it themselves.

When critics evaluate products, they elaborate on different aspects of the product such as the individuals who contributed to it. In a review, critics can provide the evaluation of a project as well as of the collaborators in it. If a high-status actor works with high-status partners, critics likely acknowledge that they work together and their role in the product. If audiences read this, they also think that many high-status actors work together on the project rather than one high-status actor makes a lot of effort on it. In other words, audiences allocate their recognition to all high-status actors who work on the project. To prevent this case, high-status actors work with low-status partners. Therefore,

*Hypothesis 3: After audiences get access to information by critics more easily, high-status social actors will work with low-status partners.*

Next, we consider if age positively moderates the relationship between high-status and tie formation with low-status partners. Older social actors have fewer productive years during which they can work and develop products. Moreover, they can be evaluated more harshly than younger ones (Cleveland & Landy, 1983). Thus, they are reluctant to invest in new capabilities (Buchholtz, Ribbens, & Houle, 2003) and take risks (Serfling, 2014). Instead, they prefer to take the established ways and approaches (Cirillo, Brusoni, & Valentini, 2014). Hence, they prefer to work per their styles.

As high-status social actors have first pick in important resources such as exchange partners, social actors who are older and high-status are more likely to select partners who will comply with or defer to them. Moreover, they may have fewer incentives to bargain/negotiate with potential high-status collaborators who may force them to compromise and change their routines. In terms of recognition, since high-status actors get more recognition for their work, older high-status actors have limited time to benefit from the extraordinary recognition associated with a high-status position. This makes them reluctant to share recognition with others.

Taken together, because of increased sharing of recognition and compromising on working style with prospective high-status partners, older high-status will not prefer to work with high-status actors. While low-status actors comply with the wishes of high-status actors and do not compete to share recognition with high-status actors. Therefore:

*Hypothesis 4: Older high-status social actors will work with low-status partners.*

## METHODS

### Research Setting: Hollywood

We test our hypotheses on the movie industry in the United States. This setting is suitable as we could observe social actors who become high-status, i.e., Oscar winners and their counterfactuals, i.e., Oscar nominees. Members of the Directors branch of the Academy of

Motion Picture Arts and Sciences “vote in the order of their preference for not more than five productions. The five motion pictures receiving the highest number of votes shall become the nominations for final voting for the Directing award. Final voting for the Directing award shall be restricted to active and life Academy members” (Oscars, 2019, Rule Ten: Special Rules for the Directing Award). After the final ballots are tabulated, only two partners of PricewaterhouseCoopers know the results until the famous envelopes are opened onstage during the Oscars telecast (Oscars, 2019, Nominations Voting Process). Thus, Oscar awards are highly publicized annual events in which awards are publicly given to winners. Winning this award is the most important and visible form of status and peer recognition in the field (Baumann, 2001). As Steven Spielberg said: "Am I allowed to say I really wanted this? This is fantastic." after winning the Oscar for the Best Director in 1998.

We draw upon the notion of the 41st chair discussed in the Matthew Effect (Merton, 1968); per this notion, in our setting the individuals who win an Oscar will likely have the same talent as those who are nominated for an Oscar. Academy Award winner for Best Director, Clint Eastwood said: "There are a lot of great movies that have won the Academy Award, and a lot of great movies that haven't. You just do the best you can.", thus, comparing Oscar winners with Oscar nominees can give us a reliable counterfactual. However, compared to Oscar nominees, Oscar winners receive a disproportionate amount of benefits for a given quality of work (Merton, 1968). For example, in movie collaborations among Oscar Winners and Oscar Nominees, the posters and trailers give much more importance to Oscar Winners than to Oscar Nominees. Some directors might win or get nominations for Oscar several times in their career. However, we thought that first time winning has a significant impact on their subsequent career. We considered first time winners and nominees in our sample.

The movie industry is characterized as a “temporal organization” or “short-term project” (Bechky, 2006). Each project represents a form of organization. After finishing one project, people working in Hollywood join a new project (Jones, 1996). Each project is relatively short-term and needs creativity and efficient production routines (Levinthal & Madsen, 2006). Since individuals' talent is not transparent, individuals tend to work with past collaborators (Ferriani, Corrado, & Boschetti, 2005) or with those who have been successful in the past (Rossman, Esparza, & Bonacich, 2010). Also, people working in this industry should maintain commercial and/or critical success (Jacobs, 1939). Finally, in this industry, two types of audiences exist: professional critics and consumers (Cattani & Ferriani, 2008; Hsu, 2006). Professional critics can significantly influence general consumers' decisions in U.S. film industry. Also, opinions of general audiences to a film can determine other general audiences' decisions and opinions. To keep commercial and/or critical success, considering these audiences are crucial.

For this study, we investigated movies produced by directors who won or were nominated Oscar for the first time in their career. Our study examines the U.S. motion picture industry and covers years from 1939 to 2020. We collected this data from IMDb (www.imdb.com). The 1st Academy Awards ceremony was held in 1929; however, until the 10th ceremony, directors could be nominated for multiple films in the same year. In 1939, the rule changed i.e., a director could be nominated for at most one movie at each ceremony. Hence, we started collecting data from 1939. In this industry, movie directors make creative decisions such as selection of casts and genres while producers are in charge of financial decisions (Blair, 2015). Thus, our unit of analysis is director-film project.

In a Q&A session, two-time Academy Award Winner for Best Actress, Jodie Foster revealed that while casting for the movie: The Silence of the Lambs, producers considered actors such as Al Pacino, Robert De Niro, Dustin Hoffman for the role of Hannibal Lecter, but director Jonathan Demme wanted Hannibal Lecter to be played by a British actor (Jodie Foster, BFI, 2017). Therefore, in this study, we consider selection of casts as choice of partners for main analysis. We also collected movie data on details of all casts of movies, screen writers, and producers from IMDb. We obtained data on Oscar ceremony date, Oscar wins, and nominations from the official website of the Academy Awards.

**Modeling strategy**

We test our hypotheses by conducting difference-in-differences (DID) analysis. We included first time Oscar winning directors as the treated group and use first time Oscar nominated directors as their counterfactuals in our sample i.e., control group. We have two periods i.e., pre and post Academy Award ceremony in our sample for a director who wins or gets nominated for the Oscar for Best Director for the first time.

**Dependent variables**

*Status of partners.* We identified actors and actresses who have ever won or have been nominated in a leading role or supporting role before the focal film has been released as higher status. We tracked three movies before and after the Oscar ceremony for a focal director was held. We calculated status of partners by taking a ratio i.e., the number of high-status partners divided by the number of total partners.

**Independent variables**

*Oscar winner.* If the director is an Oscar winner for the first time in his or her career, we coded Oscar winner as 1. If the director is an Oscar nominee for the first time in his or her career, we code this variable as 0. Even if the director gets nominated before winning, if the director wins later in his career, we considered him as a winner. On the other hand, nominees have never won Oscar. Since our unit of analysis is a director, we focused on the Academy Award for Best Directing that is annually presented by the Academy of Motion Picture Arts and Sciences. In this study, our sample includes first time nominees and winners in career of directors to capture effects of Oscar winning on partner selection of a director.

*Post.* In our sample, we have pre-Oscar and post-Oscar periods. We coded the variable as 1 if the movies are released after Oscar ceremony.

**Moderators**

Since we used a difference-in-differences approach, if we include a moderator, it becomes 3-way interaction. It is difficult for us to interpret the effect of moderators by using 3-way interaction, so we split a sample by considering above or below of median of each moderator.

*Awareness to a product.* To capture awareness to a product of film directors, we split the main sample into before and after the IMDb platform exists. IMDb platform started in 1993. We consider that general audience, critics, and professionals in the movie industry get access to detailed information of movies after this website started. Thus, we assume that, after establishment of this platform, directors pay more attention to the collaborators of their product. To test Hypothesis 2, we split the sample by identifying Oscar received year is before or after 1993.

*Information from a third-party critic.* Launched in 2001, Metacritic.com is a website that aggregates critics' evaluation to a movie. If a product is reviewed by critics, then audiences consider it to have legitimacy and thus consider it (Eliashberg & Shugan, 1997; Janssen, 1997) whereas audiences ignore products that critics have not reviewed. To consider this, similar to Awareness to a product, we split the sample by identifying whether the year of Oscar win/nomination is before or after Metacritic.com exists i.e., 2001.

*Age.* We include the age of a director by using birth year of a director from IMDb. To test Hypothesis 4, we split the sample by considering above (older directors) or below (younger directors) median of age of directors.

## Control variables

*Experiences of movie.* We counted the number of film experiences as a director. If directors have directing experiences in their past, they may know more about how to select partners.

*Experiences of TV.* We counted the number of experiences as a director for a TV episode. Movie and TV industry are somehow overlapping in terms of casts and stuff. There are distinctive differences between two industries such as award, size of budget, and way of shooting. To control for this effect, we included experience of TV programs for a director.

*Multirole in a movie.* A director usually focuses on the artistic quality of a movie and closely works with a producer who manages financial and administrative tasks of a movie (Hadida, 2010). If a director is also a producer, the director can have greater (creative) freedom in selecting genres and collaborators (Cattani & Ferriani, 2008). Similarly, if a director is also a screenwriter, then while writing the script, the director can have some idea about who can be the main actors or actresses in a movie. We included an indicator variable to control for directors who have multiple roles in movie production. If the director has a multi-role experience in 3 or 5 movies, we coded this variable as 1 and coded it as 0 otherwise.

*Structural holes.* We computed structural holes of a director by using 3 years rolling window for creating network. To make a network, we included 10 top-billed casts and crews for a movie. After calculating structural holes of a director for 3 years rolling window network by following Burt's constraint (Burt, 1992), we computed average score of structural holes for a director during pre- and post-Oscar periods. We assume that a director who has greater structural holes has more freedom of partner selection since they can get access to more information. If social actors have more structural holes, the value of structural holes is greater.

*Decade dummies.* Depending on which decade the movie is produced, the way of evaluation for Oscar can be different. For example, the compositions of evaluators can be different during 1950s and 2000s. To control for this, we included decade dummies.

## RESULTS

We report the descriptive statistics for the main variables in Table 1. The average age of directors is 46.55 years old. The average experiences of movie and TV of directors are 13 and 10 projects respectively. As we explained the variable section, in this analysis, we considered first time winners who might have been nominated in their career as winners. We included first time nominees as their counterfactuals. Hence, mean for winners is 0.29 rather than 0.2. On average one out four members of a director's team are high-status.

To check if the parallel path assumption is valid for our difference-in-differences analysis, we draw a graph in Figure 1. We traced 5 movies before and after Oscar ceremonies. In Figure 1, the fifth movie is the movie for which focal actors are nominated. X-axis is the number of movies and Y-axis is the ratio of high-status partners in the movie. From Figure 1, we can observe Oscar winners and nominees show similar trends before the Oscar ceremony while they show different paths after the Oscar ceremony. Hence, the parallel path assumption is not violated in our sample.

---Insert Table 1 & Figure 1 here---

Table 2 represents the results for Hypothesis 1. We used the diff command on Stata and checked if there are differences in status of partners between treated group and control group and pre-Oscar and post-Oscar. We find significant differences in selection of status of partners. After winning Oscar, social actors are more likely to select lower status partners compared to Oscar nominees ($\beta$ = - 0.090, $p < 0.05$). This supports Hypothesis 1.

---Insert Table 2 here---

Table 3 shows the OLS regression results for Hypothesis 1 and placebo check. Model 1 includes only control variables. As age of a director increases, the director works with higher status of partners (β = 0.0041, $p < 0.01$). When a unit of experience of movies for a director increases, the director works with lower status of partners (β = - 0.0026, $p < 0.01$). On the other hand, directors who are in open network work with lower status of partners (β = - 0.3405, $p < 0.01$). Model 2 adds Status and Post to variables in Model 1. We find that after winning an Oscar, directors decrease working with high-status partners (β = - 0.0902, $p < 0.05$). We interpret this: the status of the team of an Oscar winning director decreases by 9% (i.e., 36% decrease relative to the sample mean). Consistent with Table 2, this supports for Hypothesis 1.

Model 3 shows a placebo test for Hypothesis 1. We selected sample period that no directors experience Oscar winning by tracking their further older movies. We tracked 6 movies (we used 3 movies before Oscar winning as post and 3 further older movies as pre). In this sample of placebo test, we gave the directors who experience Oscar winners in Model 2 as pseudo winners and remaining directors as nominees as their counterfactuals. We expected that we did not receive any significant results since these pseudo-Oscar winners did not experience positive status shifts. As we expected, in Model 3, the coefficient of Status X Post is insignificant. Hence, we could observe that Oscar winning experience significantly influence the selection of status of partners.

---Insert Table 3 here---

Table 4 represents the OLS regression results for Hypothesis 2. Model 1 shows the result of Hypothesis 1. In Models 2 and 3, to capture the awareness to movies, we split the sample before or after IMDb platform has started i.e., 1993. We expected that directors who win an Oscar will work with lower status partners after IMDb platform launched i.e., increased awareness to movies. In Model 3, we find that directors who win Oscar will work with lower status partners after 1993. The coefficient of Status X Post in Model 3 ($\beta$ = - 0.1665, $p < 0.05$) is 1.84 times greater than that in Model 1. Hence, Hypothesis 2 is supported.

In Models 4 and 5, we split the sample before and after Metacritic.com started in 2001 i.e., more information by critics. In Model 5, after 2001, Oscar winning directors work with lower status partners. The coefficient of Status X Post in Model 5 ($\beta$ = - 0.1843, $p < 0.05$) is also 2.04 times greater than that in Model 1. These results suggest that after audiences get access to information by critics more easily, i.e., launch of Metascore.com, Oscar winning directors work with low-status partners. Therefore, Hypothesis 3 is supported.

---Insert Table 4 here---

Table 5 represents the OLS regression results for Hypothesis 4. Model 1 shows the result of Hypothesis 1. To test how older directors can strengthen the relationship between Oscar winning and selection of lower status of partners, we split the sample by using the median of age of directors as a threshold. Model 2 includes the young directors while Model 3 includes older directors. In Model 3, we find that after winning Oscar, older directors are more likely to work with lower status of partners ($\beta$ = - 0.1311, $p < 0.05$). Hence, Hypothesis 4 is supported.

---Insert Table 5 here---

**Robustness check**

For the main analysis, we tracked 3 movies to capture if social actors work with existing partners or high-status partners. For a robustness check, instead of 3 movies, we tracked 5 movies. We considered partners as top-billed actors and actresses similar to main analysis. Table 6 shows the robustness results for Hypothesis 1 by using diff command with Stata. As we expected in the hypothesis, after becoming high-status, social actors work with lower status partners ($\beta$ = - 0.059, $p < 0.10$). Our sample size is 420. We interpret this as: the status of the team of an Oscar winning director decreases by about 6% (i.e., 24% decrease relative to the sample mean). Despite a relatively small sample size, we think we can interpret robustness check result for Hypothesis 1.

---Insert Table 6 here---

Table 7 represents the regression results for robustness check of Hypotheses 1, 2, and 3. Model 1 shows the robustness check result of Hypothesis 1. The coefficient of Status X Post is negative ($\beta = -0.0592$, $p < 0.10$). Hence, we find that after winning an Oscar, directors work with lower status partners. As in Table 4, to avoid interpreting a 3-way interaction, we split the sample by using before/after each platform launched. Models 2 and 3 show results for the IMDb platform while Models 4 and 5 include results for Metacritic.com. From Models 3 and 5, we find that the coefficient of Status X Post is significant and negative (Model 3: $\beta = -0.1264$, $p < 0.05$, Model 5: $\beta = -0.1359$, $p < 0.10$). As we expected in Hypothesis 2, after winning Oscar, directors work with lower status partners after the awareness to movies increases. Also, as we expected in Hypothesis 3, after winning Oscar, directors work with low status partners after critics provide more information about movies.

---Insert Table 7 here---

Table 8 shows the regression results for robustness check of Hypothesis 4. To avoid 3-way interaction, we split the sample by using median of age of directors as a cut-off point. Model 1 is full model. Model 2 has the sample for younger directors while Model 3 includes the sample for older directors. From this analysis, we find that older directors work with lower status partners (Model 3: $\beta = -0.1076$, $p < 0.05$). Hence, Hypothesis 4 is supported.

---Insert Table 8 here---

## DISCUSSION

In this study, we find that compared to Oscar-nominated directors, Oscar winning directors, i.e., high-status, are more likely to select low-status partners in their following products. To do so, we conduct a difference-in-differences analysis. By focusing on first-time Oscar winners and nominees, we could compare winners i.e., high-status with counterfactuals i.e., nominees, low-status. We argue that high-status social actors work with lower status partners. This is because they can avoid competition for recognition with high-status partners and these actors can show who are the main contributors in their following work by working with lower-status partners. We also consider three situations that can strengthen the selection of lower status partners by high-status actors. When awareness to the product increases, third party critics provide more information, and high-status social actors are older, they are more likely to work with low-status partners. Since their work is evaluated by people in the same industry and audience, it is crucial for social actors who become high-status to express who are the main contributors in their work.

### Contributions

We provide some potential contributions to extant research on status and selection of partners. This study attempts to understand why social actors form a status heterophilous ties. Previous research has shown that high-status actors can work with other high-status actors, i.e. homophily (Podolny, 1994; Podolny & Phillips, 1996). Also, researchers have studied how and why social actors work with low-status actors, i.e. heterophily (Castellucci & Ertug, 2010; Shipilov et al., 2011). However, no research has conducted to investigate how and why social actors who become suddenly high-status select low-status partners. By arguing that high-status actors prefer to avoid the competition for recognition with high-status, our result supports that they work with lower-status partners. We can observe that recognition can play a role in selection of partners by high-status actors.

This study also considers two audiences such as consumers and critics by considering presence of IMDb and Metacritic platform. Presence of these platforms can increase the awareness to the product and information about it. Therefore, after these platforms are launched, high-status social actors are more likely to work with low-status partners. By considering these situations, we can more deeply understand how high-status social actors try to receive their recognition from audiences by selecting proper partners.

**Limitations and future research**

Our study has several limitations. First, we used partners as main actors and actresses in our results of main analysis. However, in movie industry, backstage-staffs and front-stage staffs exist. Front-stage staffs are actress and actors who are visible to audiences. Back-stage-staffs are cinematographers, editors, producers, and screen writers (Perretti & Negro, 2007). We believe that recognition is more related to front-stage staffs since they are visible to audience and consumers. Hence, it is reasonable to consider actors and actresses in our analysis. However, if we can anticipate that directors have different expectations from back-stage-staffs, it will be interesting to observe the difference in selection of status of partners between front-stage and back-stage-staffs in future research.

Second, our focus is on the consequences of first Oscar winning on partner selection. However, some directors win or get nominated Oscar several times. If we consider these directors in the future, we might find different way of partner selection after they get multiple winning or nominations.

Third, in our study, we focus on Oscar winner and Oscar nominees for the first time for their career. However, in movie industry, there are directors who have never got nominated. We do not include them because we would like to examine the consequences of winning Oscar on partner selection by comparing to nominees. However, if we include non-nominated directors, we might find different way of partner selection since status does not exert pressures to all social actors equally. According to middle-status conformity theory (Phillips & Zuckerman, 2001), there is a U-shaped relationship between status and deviant behavior.

Despite these limitations, this is among the first study that investigates how actors who become high-status select new partners.

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**Table 1.** Summary Statistics

| | Mean | SD | Max | Min | P25 | P50 | P75 | P90 |
|---|---|---|---|---|---|---|---|---|
| Status | 0.29 | 0.45 | 1 | 0 | 0 | 0 | 1 | 1 |
| Post | 0.50 | 0.50 | 1 | 0 | 0 | 0.50 | 1 | 1 |
| Age | 46.55 | 8.89 | 80 | 23 | 41 | 46 | 51 | 57 |
| Experience of movies | 12.94 | 16.74 | 140 | 1 | 4 | 8 | 14 | 30 |
| Experience of TV | 9.40 | 35.63 | 449 | 0 | 0 | 0 | 5 | 21 |
| Multirole in a movie | 0.39 | 0.49 | 1 | 0 | 0 | 0 | 1 | 1 |
| Structural holes | 0.16 | 0.09 | 1 | 0.03 | 0.09 | 0.14 | 0.20 | 0.25 |
| Status of partners | 0.25 | 0.19 | 1 | 0 | 0.08 | 0.25 | 0.33 | 0.50 |

Structural holes are computed over 3 movies, 3 year rolling window

**Figure 1.** Parallel path assumption check

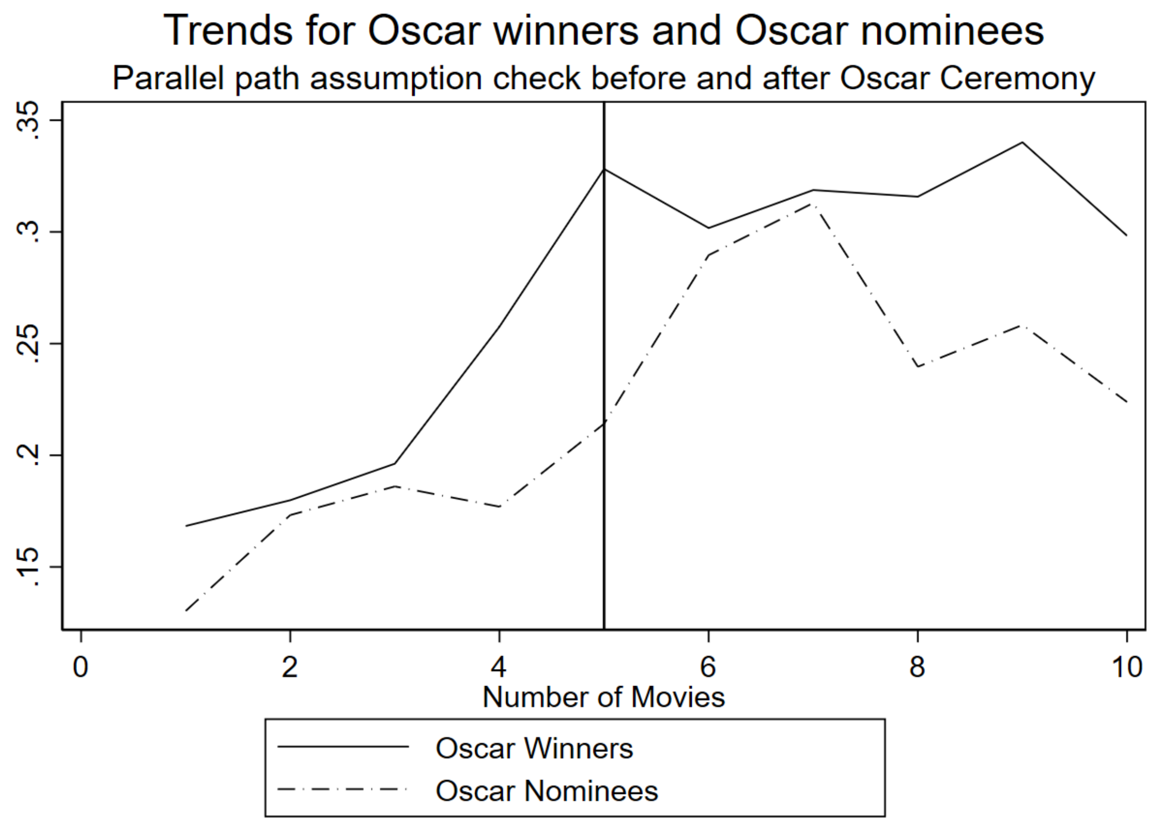


**Table 2.** Results for Hypothesis 1

| | | Pre-Oscar | Post-Oscar | Difference |
|---|---|---|---|---|
| Status of partners | Control | 0.120 | 0.206 | -0.086 |
| (N=420) | Treatment | 0.210 | 0.206 | -0.004 |
| R-square: 0.15 | Difference | 0.090*** [0.029] | -0.001 [0.026] | -0.090** [0.038] |

Robust standard errors are in parentheses, $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. We include controls.

**Table 3.** Status of Partners and Placebo check

Dependent Variable: Status of partners (ratio: bigger value indicates high-status partners)

| | Model 1<br>Only Controls | Model 2<br>Hypothesis 1 | Model 3<br>Placebo test |
|---|---|---|---|
| Status | | $0.0897^{***}$ | $0.1422^{***}$ |
| | | (0.0290) | (0.0459) |
| Post | | $0.0862^{***}$ | $0.1958^{***}$ |
| | | (0.0218) | (0.0348) |
| Status X Post | | $-0.0902^{**}$ | -0.1032 |
| | | (0.0381) | (0.0638) |
| Age | $0.0041^{***}$ | $0.0034^{***}$ | 0.0066** |
| | (0.0013) | (0.0012) | (0.0027) |
| Experience of movies | $-0.0026^{***}$ | $-0.0025^{***}$ | $-0.0020^{**}$ |
| | (0.0008) | (0.0008) | (0.0009) |
| Experience of TV | 0.0001 | 0.0001 | -0.0003 |
| | (0.0002) | (0.0002) | (0.0003) |
| Multirole in a movie | 0.0217 | 0.0111 | -0.0175 |
| | (0.0193) | (0.0190) | (0.0390) |
| Structural holes | $-0.3405^{***}$ | $-0.2997^{***}$ | 0.0008 |
| | (0.1142) | (0.1125) | (0.0906) |
| Decade dummies | Yes | Yes | Yes |
| Observations | 420 | 420 | 117 |
| Log likelihood | 121.9063 | 132.7551 | 61.3807 |

Robust standard errors in parentheses, $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. Structural holes are computed over 3 movies, 3 year rolling window

**Table 4.** The moderating effects of presence of IMDb and Metacritic platform

Dependent Variable: Status of partners (ratio: bigger value indicates high-status partners)

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | Full | IMDb platform | | Metacritic platform | |
| | | Before 1993 | After 1993 | Before 2001 | After 2001 |
| Status | 0.0897*** | 0.0812** | 0.1000** | 0.0988*** | 0.0732 |
| | (0.0290) | (0.0381) | (0.0427) | (0.0338) | (0.0532) |
| Post | 0.0862*** | 0.0577** | 0.1334*** | 0.0682*** | 0.1451*** |
| | (0.0218) | (0.0274) | (0.0357) | (0.0232) | (0.0525) |
| Status X Post | -0.0902** | -0.0442 | -0.1665** | -0.0627 | -0.1843** |
| | (0.0381) | (0.0458) | (0.0658) | (0.0417) | (0.0838) |
| Age | 0.0034*** | 0.0048** | 0.0033* | 0.0047*** | 0.0031 |
| | (0.0012) | (0.0019) | (0.0019) | (0.0016) | (0.0025) |
| Experience of movies | -0.0025*** | -0.0028*** | -0.0024 | -0.0026*** | -0.0037 |
| | (0.0008) | (0.0009) | (0.0037) | (0.0008) | (0.0044) |
| Experience of TV | 0.0001 | 0.0002 | -0.0058*** | 0.0002 | -0.0065*** |
| | (0.0002) | (0.0002) | (0.0016) | (0.0002) | (0.0019) |
| Multirole in a movie | 0.0111 | 0.0204 | -0.0272 | 0.0191 | -0.0353 |
| | (0.0190) | (0.0234) | (0.0342) | (0.0203) | (0.0457) |
| Structural holes | -0.2997*** | -0.1516 | -0.5384** | -0.1471 | -0.6673** |
| | (0.1125) | (0.1321) | (0.2078) | (0.1212) | (0.2617) |
| Constant | 0.1202* | 0.1055 | 0.2179** | 0.0919 | 0.2732** |
| | (0.0653) | (0.1234) | (0.0937) | (0.1150) | (0.1251) |
| Decade dummies | Yes | Yes | Yes | Yes | Yes |
| Observations | 420 | 258 | 162 | 315 | 105 |
| Log likelihood | 132.7551 | 93.5325 | 50.2828 | 123.7311 | 24.4076 |

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, Structural holes are computed over 3 movies, 3 year rolling window

**Table 5.** The moderating effect of age

| | Dependent variable: Status of partners (3 movies before/after Oscar) | | |
|---|---|---|---|
| | Model 1<br>Main analysis | Model 2<br>Younger directors | Model 3<br>Older directors |
| Status | 0.0897*** | 0.1090*** | 0.0952** |
| | (0.0290) | (0.0396) | (0.0410) |
| Post | 0.0862*** | 0.0896*** | 0.0803** |
| | (0.0218) | (0.0292) | (0.0330) |
| Status X Post | -0.0902** | -0.0314 | -0.1311** |
| | (0.0381) | (0.0513) | (0.0531) |
| Age | 0.0034*** | | |
| | (0.0012) | | |
| Experience of movies | -0.0025*** | 0.0020 | -0.0025*** |
| | (0.0008) | (0.0015) | (0.0009) |
| Experience of TV | 0.0001 | -0.0007 | 0.0001 |
| | (0.0002) | (0.0006) | (0.0003) |
| Multirole in a movie | 0.0111 | 0.0246 | 0.0079 |
| | (0.0190) | (0.0273) | (0.0282) |
| Structural holes | -0.2997*** | -0.2124* | -0.2759 |
| | (0.1125) | (0.1093) | (0.2422) |
| Constant | 0.1202* | 0.1940*** | 0.3165*** |
| | (0.0653) | (0.0561) | (0.0616) |
| Decade dummies | Yes | Yes | Yes |
| Observations | 420 | 200 | 220 |
| Log likelihood | 132.7551 | 83.2263 | 61.6011 |

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Structural holes are computed over 3 movies, 3 year rolling window

**Table 6.** Robustness check results for Hypothesis 1

| | | Pre-Oscar | Post-Oscar | Difference |
|---|---|---|---|---|
| Status of partners | Control | 0.137 | 0.220 | 0.083 |
| (N=420) | Treatment | 0.205 | 0.229 | 0.024 |
| R-square: 0.10 | Difference | 0.068*** [0.026] | 0.008 [0.022] | -0.059* [0.034] |

Robust standard errors are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. We included all controls.

**Table 7.** Robustness check for the moderating effects of IMDb and Metacritic platform

| | Dependent variable: Status of partners (5 movies before/after Oscar) | | | | |
|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| | Full model | IMDb platform | | Metacritic platform | |
| | | Before 1993 | After 1993 | Before 2001 | After 2001 |
| Status | 0.0676*** | 0.0617* | 0.0846** | 0.0817*** | 0.0465 |
| | (0.0259) | (0.0346) | (0.0372) | (0.0315) | (0.0430) |
| Post | 0.0831*** | 0.0587** | 0.1269*** | 0.0702*** | 0.1303** |
| | (0.0198) | (0.0239) | (0.0339) | (0.0204) | (0.0510) |
| Status X Post | -0.0592* | -0.0182 | -0.1264** | -0.0402 | -0.1359* |
| | (0.0336) | (0.0403) | (0.0598) | (0.0379) | (0.0706) |
| Age | 0.0024** | 0.0027* | 0.0029 | 0.0033** | 0.0025 |
| | (0.0011) | (0.0016) | (0.0018) | (0.0013) | (0.0024) |
| Experience of movies | -0.0014** | -0.0013** | -0.0029 | -0.0013** | -0.0042 |
| | (0.0006) | (0.0006) | (0.0033) | (0.0006) | (0.0038) |
| Experience of TV | 0.0002 | 0.0002* | -0.0044*** | 0.0002 | -0.0047*** |
| | (0.0001) | (0.0001) | (0.0014) | (0.0001) | (0.0016) |
| Multirole in a movie | 0.0131 | 0.0305 | -0.0252 | 0.0220 | -0.0234 |
| | (0.0170) | (0.0205) | (0.0299) | (0.0181) | (0.0394) |
| Structural holes | -0.4234*** | -0.5973*** | -0.3792* | -0.4637*** | -0.4944 |
| | (0.1581) | (0.1863) | (0.2190) | (0.1608) | (0.2997) |
| Constant | 0.1374** | 0.1737** | 0.1529* | 0.1320 | 0.2096* |
| | (0.0636) | (0.0881) | (0.0878) | (0.0849) | (0.1199) |
| Decade dummies | Yes | Yes | Yes | Yes | Yes |
| Observations | 415 | 253 | 162 | 310 | 105 |
| Log likelihood | 180.7524 | 129.4587 | 62.5520 | 160.9769 | 34.1320 |

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, Structural holes are 5 movies and 5 years-rolling window.

**Table 8.** Robustness check for moderating effect of age

| | Dependent variable: Status of partners (5 movies before/after Oscar) | | |
|---|---|---|---|
| | Model 1<br>Main analysis | Model 2<br>Young directors | Model 3<br>Older directors |
| Status | 0.0676*** | 0.0749** | 0.0900** |
| | (0.0259) | (0.0368) | (0.0346) |
| Post | 0.0831*** | 0.0792*** | 0.0851*** |
| | (0.0198) | (0.0260) | (0.0302) |
| Status X Post | -0.0592* | 0.0002 | -0.1076** |
| | (0.0336) | (0.0448) | (0.0466) |
| Age | 0.0024** | | |
| | (0.0011) | | |
| Experience of movies | -0.0014** | 0.0018 | -0.0013* |
| | (0.0006) | (0.0016) | (0.0007) |
| Experience of TV | 0.0002 | -0.0002 | 0.0000 |
| | (0.0001) | (0.0006) | (0.0002) |
| Multirole in a movie | 0.0131 | 0.0429* | 0.0006 |
| | (0.0170) | (0.0253) | (0.0245) |
| Structural holes | -0.4234*** | -0.3076** | -0.3407 |
| | (0.1581) | (0.1495) | (0.3650) |
| Constant | 0.1374** | 0.1809*** | 0.2670*** |
| | (0.0636) | (0.0546) | (0.0570) |
| Decade dummies | Yes | Yes | Yes |
| Observations | 415 | 194 | 221 |
| Log likelihood | 180.7524 | 108.6394 | 84.6173 |

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Structural holes are computed over 5 movies, 5 year rolling window

**Shine a spotlight on: New technology adoption when social actors receive less recognition**

ABSTRACT

I investigate how social actors adopt and select new technology when they receive less recognition to their product(s) compared to their past. Performance-feedback theory explains that when social actors perform below their aspirations, they are more likely to change their behavior to improve their performance. Consistent with this theory, I argue that social actors who receive less recognition decide to adopt new technology by expecting to improve their recognition. Also, social actors who receive significantly less recognition adopt new technology in riskier fields. I tested these hypotheses by focusing on digital camera adoption in Hollywood film industry between 2000 and 2010.

Keywords: Recognition loss, performance-feedback theory, technology adoption

## INTRODUCTION

Recognition is defined as a public judgement about the quality of the recipient's work (Heinich, 2009). If social actors receive more recognition, they can get benefits such as more sales (Gemser, Leenders, & Wijnberg, 2008; Kovács & Sharkey, 2014), more options for working with others (Piazza & Castellucci, 2014), increased attention of their work (Azoulay, Stuart, & Wang, 2013; Reschke, Azoulay, & Stuart, 2018), and increased revenue for a given level of performance (Benjamin & Podolny, 1999). Social actors can enhance their recognition by receiving awards. Awards play a crucial role in signaling the quality of products and service to consumers and audience in a variety of fields (Azoulay et al., 2013; Jensen & Kim, 2015; Reschke et al., 2018). When the quality of products and services is not clear before they actually experience them, consumers and audience infer the quality of a product from the awards that its producers have received (Kovács & Sharkey, 2014; Sharkey & Kovács, 2018). In this way, awards can also increase the recognition of products and bring them into the focus of consumers and audiences.

However, studies on recognition have not examined how social actors manage their recognition when they receive less recognition. As I explained earlier, recognition can provide benefits to social actors. If social actors can maintain or improve recognition, they can receive the potential benefits associated with high recognition. On the other hand, if they lose recognition, their performance may eventually decrease. Therefore, I investigate how social actors try to recover their recognition when they receive less recognition.

Performance-feedback theory explains that when social actors receive negative feedback, i.e. their performance is below their aspirations, they take more risks to improve their performance (Greve, 1998; Greve & Gaba, 2017). This tendency becomes stronger as their performance is increasingly below their aspirations. This is because social actors expect that by taking greater risks, they can receive greater rewards i.e. performance gains that can help them offset the difference between their poor performance and their aspirations. Studies on performance-feedback often consider financial performance (Greve & Gaba, 2017), but recently they have increased their focus on non-financial performance dimensions such as organizational failures and size (Baum & Dahlin, 2007; Greve, 2008). Since recognition is related to performance of social actors (Gemser et al., 2008; Sharkey & Kovács, 2018) and can help social actors improve their performance, it is reasonable to connect recognition with non-financial performance when thinking of aspirations and performance. Hence, I argue that when social actors receive less recognition compared to their past, they need to recover this loss in recognition. Next question is how they do they take risks to offset losses in recognition. I argue that social actors adopt new technology by showing their audiences that they take risks and try to recover their recognition.

Literature on adoption of a new technology illustrates that technology adopters face risks (Attewell, 1992). These risks are related to lack of information about new technology (Greve, 2009) and possibilities to disrupt early adopters' routines (Edmondson, Bohmer, & Pisano, 2001). Depending on the risk preference of social actors (Mansfield, 1961), they can adopt a new technology earlier than others. Early adopters of new technology tend to receive economic and technological benefits (Tolbert & Zucker, 1983). Thus, early adopters face substantial risks but also expect considerable benefits; this situation is aligned with the performance-feedback theory. Early adopters of new technology can gain more attention from their peers since they are willing to collect more information about technology by observing the early adopters (Greve, 2009; Greve & Taylor, 2000). Adopting new technology can involve disruption in established routines, capabilities, and skills (Edmondson et al., 2001); however, compared to those who have not adopted the new technology, early adopters now know how to use it. Therefore, early adopters can increase their competitive advantage over their peers

(Greve, 2009) since others need to take time to observe and successfully imitate early adopters successful adoption of the new technology. Since peers attempt to imitate early adopters, early adopters can thus receive increased attention from their audiences and recognition from audiences. Hence, I argue that social actors who receive less recognition will adopt new technology.

I test these hypotheses by using data on the adoption of digital cinema cameras by film production teams in the Hollywood movie industry in the 2000s. First, in this sample period, there was controversy among filmmakers concerning the value of adopting digital cinema cameras and the resulting artistic impact even though adopting digital cinema camera can increase efficiency of production process (Murphy, 2012). Second, many awards in this industry enable me to measure different levels of recognition over time. I find that social actors who receive less recognition are more likely to adopt new technology and when the gap between their current recognition and past recognition is greater, they are more likely to adopt new technology in risker genres.

From the findings, this study advances the literature on recognition. Recognition studies have demonstrated that social actors can receive benefits after getting higher recognitions (Gemser et al., 2008; Kovács & Sharkey, 2014). Little is known about how they can manage and recover their recognitions. By connecting performance-feedback and adoption of new technology, I try to explain the mechanism.

Second, this study assumes that not all awards can enhance the recognition of a product in a similar way. As previous study has examined, specific type of award can increase purchase of products compared to when social actors receive other types of awards (Gemser et al., 2008). However, no study has conducted by considering all kinds of awards that social actors have received. There are many types of awards in cultural fields. In this study, by collecting data on all awards that cinematographers and directors have received in 2000s, I can capture the different levels of recognition by developing award-based network. This enables me to contribute to the performance-feedback literature by adding new non-financial performance measure (Greve & Gaba, 2017).

## THEORY AND HYPOTHESES

### Recognition and awards

Awards serve as crucial mechanisms for shaping the prestige structure of various fields (Azoulay et al., 2013; Jensen & Kim, 2015; Reschke et al., 2018). By receiving awards, social actors can enhance their recognition particularly in cultural fields. Well-known examples of awards in cultural fields are the Academy Awards (e.g., Cattani, Ferriani, & Allisonc, 2014; Jensen & Kim, 2015; Rossman & Schilke, 2014), the Booker Prize (Kovács & Sharkey, 2014; Sharkey & Kovács, 2018), the Grammy awards (Anand & Watson, 2004), and the Nobel Prize (Merton, 1968). Recognition is defined as a public judgement about the quality of the recipient's work (Heinich, 2009). Receiving more recognition from these awards is thus important for social actors who produce products.

First, products of these social actors compete for the attention of consumers with those of other producers (Häubl & Trifts, 2000; Oestreicher-Singer & Sundararajan, 2012). Once producers receive more recognition from winning awards, their products have greater possibilities to be consumed/used by consumers (Kovács & Sharkey, 2014). Second, awards can signal the quality of product. Consumers cannot perceive the quality of a product before experiencing it (Podolny, 1993). After a producer wins an award, consumers start perceiving the product and its producer to have high quality. Third, receiving higher recognition can provide benefits such as increasing sales (Kovács & Sharkey, 2014; Sharkey & Kovács, 2018), revenue (Gemser et al., 2008), attention (Azoulay et al., 2013; Reschke et al., 2018), and more opportunities of working with new people (Piazza & Castellucci, 2014).

Previous studies have shown that consumers roughly screen the alternatives of products (Kovács & Sharkey, 2014; Sharkey & Kovács, 2018). To select a product, they use information about the conformity of the product with norms (Phillips & Zuckerman, 2001; Zuckerman, 1999), social proof (Cialdini, 1987), status of producers (Podolny, 1993), and popularity of the product (Banerjee, 1992). Because of this screening procedure of consumers, it is important for producers to receive an award, which helps consumers to reduce their information asymmetry between consumers and producers (Karpik, 2010; Rossman & Schilke, 2014).

However, not all awards are similarly prestigious and equally increase recognition of award-receivers. Indeed, Gemser, Leenders, & Wijnberg (2008) show that the type of award that producers receive, e.g. peer-selected, consumer-selected, and expert-selected award, can provide different levels of credibility and salience to their products. Therefore, some awards more effectively signal the quality of the product to consumers than other awards. For example, in the movie industry, if cinematographers are nominated for an Oscar or a Golden Globe, they receive more recognition compared to the recognition they get from nominations in smaller movie festivals or award ceremonies. This is because consumers are more likely to watch a movie because it was nominated for an Oscar rather than because it received recognition at other ceremonies. Hence, when social actors receive less recognition, they might face consequences such as decreased revenue from their products and lower demand for their services.

Even though previous research has illustrated that winning different types of award can improve the winner's revenue after receiving an award (Gemser et al., 2008), little is known about how social actors try to improve their recognition when they receive a less recognized award. This is worth examining given the benefits of recognition mentioned previously. Also, past research has focused on a selected (13 awards) set of awards (Gemser et al., 2008). To capture recognition, in this study, I develop a network of awards by using all kinds of awards in the movie industry. Social network analysis has received attention from researchers across fields as diverse as business, economics, political science, and physics. Recently, these researchers apply social network analysis to various networks such as networks of products (Oestreicher-Singer & Sundararajan, 2012), blogs (Mayzlin & Yoganarasimhan, 2012), motion pictures (Max Wei, 2020), and patent (Funk & Owen-Smith, 2017). These studies suggest that producers exploit their network position to try to gain attention from their consumers (Mayzlin & Yoganarasimhan, 2012; Oestreicher-Singer & Sundararajan, 2012).

In this study, I assume that if an award occupies highly central positions in a network of awards, the recognition from winning or being nominated for that award is greater than from winning or being nominated for an award that occupies a less central position in that network. I also assume that once social actors receive an award, they receive recognition that comes from that award. Based on these assumptions, I examine how social actors who receive less recognition try to improve their recognition by referring to performance-feedback theory.

**Performance-feedback and change**

Performance-feedback literature explains how social actors assess their performance (Baum, Rowley, Shipilov, & Chuang, 2005; Cyert & March, 1963; Greve, 1998; Shinkle, 2012). Social actors change their behavior based on feedback that is determined by comparing their performance with their aspirations, which are "the smallest outcome that would be deemed satisfactory by decision maker" (Schneider, 1992: 1053). Due to bounded rationality, social actors try to evaluate their performance by classifying their situation in a simple way such as success or failure (Greve, 2003). When social actors perform lower than their aspirations, they consider this situation as failure. The gap between their performance and aspirations motivates them to make greater efforts to change this situation (Lant, Milliken, & Batra, 1992). To improve their performance and solve their problems, they change their behavior (Kacperczyk, Beckman, & Moliterno, 2015) and take risks (Bromiley, 1991).

On the contrary, when their performance meets their aspirations, they are less likely to search and change because they consider this situation as success. Research on performance-feedback has studied various types of change such as changes in routines (Døjbak H\aakonsson et al., 2016), strategy (Greve, 1998), partners (Baum et al., 2005), and adoption of new technology.

Many studies on performance-feedback consider financial performance feedback (Greve & Gaba, 2017). However, recently research has increased focus on non-financial performance measures such as status (Baum et al., 2005), safety (Baum & Dahlin, 2007), organization size (Greve, 2008), and product quality (Parker, Krause, & Covin, 2017). Consistent with this, I focus on recognition that derives from the awards that social actors will receive for their work. Recognition can provide benefits to social actors (Azoulay et al., 2013; Gemser et al., 2008). It is crucial for them to manage it to increase their performance.

**Performance-feedback and new technology adoption**

When a new technology is introduced in a market, it is unclear how valuable it is and how it works. As uncertainty of innovation increases, the adoption of innovation can be delayed (Greve, 2009). If social actors adopt the new technology in the initial phase of diffusion process i.e. early adopters of the new technology (Rogers, 1995), they pursue economic or technical benefits (Tolbert & Zucker, 1983). They may need to change or even abandon previous production processes, related skills, and routines (Canato, Ravasi, & Phillips, 2013; Edmondson et al., 2001). Because of the change, they might receive negative reaction from consumers (Carroll & Swaminathan, 2000). Thus, adoption of the new technology has high risk. However, social actors who decide if they adopt a new technology have different risk preferences and assessments to the technology, some of them can adopt it (Mansfield, 1961). This is because adopting new technology can give benefits to social actors (Mansfield, 1961).

First, by using new technology, they can receive more attention. Since the technology is new, many competitors and audience are willing to get more information of the technology (Angst, Agarwal, Sambamurthy, & Kelley, 2010; Greve, 2005; Greve & Taylor, 2000; Strang & Soule, 1998). In this way, people pay attention to adoption of new technology.

Second, if the new technology works well for their product compared to other adopters, early adopters can maintain competitive advantage over their rivals (Greve, 2009). For example, if social actors can improve efficiency of their work with new technology (Xue, Hitt, & Chen, 2011), they can introduce new products in a market quicker than their competitors or improve their quality of product with their new technology. Especially, when procedures of adopting a new technology are complicated, early adopters accumulate skills and knowledge that others cannot easily and quickly imitate. Therefore, social actors who quickly adopt new technology receive more competitive advantage (Rivkin, 2001) and thus expect increased recognition.

When social actors whose products receive less recognition than their aspirations, they feel the need to improve their recognition. By taking risks, they expect that they can receive rewards i.e. enhancing their recognition. Hence, consistent with performance-feedback theory, I argue that the actors whose recognition is less than their aspirations are more likely to adopt new technology to improve their recognition. Even though adopting new technology in the early timing of diffusion can be highly risky, they expect that they can change their status quo and enhance their recognition as their rewards. Hence, I hypothesize as follows.

*Hypothesis1. Social actors whose product receives less recognition than previous one will adopt new technology.*

In Hypothesis 1, I expect that social actors who receive less recognition compared to their aspirations will adopt new technology.

In this hypothesis, I consider social actors whose quality of product significantly receives less recognition compared to their aspirations. Performance-feedback theory demonstrates that as differences between performance and aspirations of social actors increase i.e. they receive stronger negative feedback, they are more likely to change their behavior and become risk-takers (Greve & Gaba, 2017). This is because they want to improve their situation by taking higher risk options. I apply this logic to this study. Thus, I expect that social actors whose product significantly receives less recognition will change their technology in more risky fields. More risky fields mean that other social actors have not adopted new technology in these specific fields, so social actors cannot predict what will happen after adopting new technology. Performance-feedback theory suggests that the gaps between actual performance and aspirations of social actors are greater, these social actors take more risks (Baum et al., 2005; Greve & Gaba, 2017). This is because social actors whose performance further below to their aspirations recognize that they should change and improve their current situation and expect to get rewards for taking risks. In this study, adopting new technology in these fields can be riskier but these social actors expect that their recognition will be recovered after taking risks. Therefore, I hypothesize as follows.

*Hypothesis 2: Social actors whose product significantly receives less recognition will adopt new technology in more risky fields.*

METHODS

## Data

From the Internet Movie Database (https://www.imdb.com/), I collected data on films and film production teams, consisting of cinematographers and directors, who are responsible for making adoption of digital cinema camera. I include movies that are produced by major film production companies such as DreamWorks, MGM, Paramount, Sony, 20th Century Fox Film Corporation, Universal, Walt Disney, and Warner Bros in this study. These films are released in the US from January 1, 2000 to December 31, 2010 and excluded films with no camera used in production (e.g. animation movies).

I chose this research context for the following reasons. First, the period I analyzed in this study Hollywood experienced a transition in cinema cameras: from analog to digital ones. Figure 1 shows the cumulative number of films for which digital cinema cameras were used during our observation period. This suggests that this period was the early phase of digital camera adoption. Of the 136 films released in 2000, the proportion made with digital cinema cameras was 1.4%. Although the proportion jumped to 23% in 2010, approximately 75% of films released in that year did not use digital cinema cameras. The first major studio film that used digital technology was Star Wars: Episode 2 in 2002, directed by George Lucas. From that time, the number of adopters increased, but in this early phase of diffusion, there was controversy among filmmakers concerning the value of adopting digital cinema cameras and the resulting artistic impact (Murphy, 2012).

Digital cinema cameras are different from the analog ones in several ways (Lyman, 2001). With digital cinema cameras, film production teams can edit the scenes easily with other digital technologies for special effects, color adjustment, and image fixing. For example, "a director can shift the perspective of a scene, add a fresh camera movement, alter an actor's performance, transfer the location from Red Square to Times Square, speed up time, slow it down and generally do whatever schedule and budget allow to get the desired images up there on the screen" (Lyman, 2001). Moreover, because digital cinema cameras do not require frequent reloads of film during shooting, their "capturing" time can be much longer, allowing film production teams to create and develop new ways of "shooting films" (Kirsner, 2006). In addition, the proponents of digital production pointed out the efficiency advantages in terms of production time, budgets for shooting, and costs of film purchases and development.

Nevertheless, some filmmakers viewed digital cinema cameras negatively, claiming that the shift to digital production required destructive changes in production processes. For example, one French cinematographer commented that: "It's really a very big change to move from film to digital. The images don't have the same texture, the poetic charge is different, so you have to reinvent the images" (Hohenadel, 2012). Another concern was digital cinema cameras' poor picture quality, at least at the outset of the diffusion process. A New York Times article in 2001 noted that "Many filmmakers are convinced that celluloid film is still far superior to digital videotapes in tone, texture, color and the capacity to resolve detail and complex patterns" (Bailey, 2001). This concern has been addressed elsewhere as well: 'digital images feel colder than the more lush images on films'(Lyman, 2001); film cinema cameras can capture "bright sunlight in a more nuanced ways", whereas "digital cameras do not have the resolution found in film" (Kirsner, 2006). Indeed, for these reasons, Steven Spielberg, an icon of the industry, was a strong opponent of digital cinema cameras at that time. Thus, film production teams faced uncertainties when adopting digital cinema cameras.

The second reason I chose our research context was that this industry offers a context in which there are multiple awards for film production team such as cinematographers and directors. In our sample, there are 361 awards for cinematographers and 775 awards for directors. I assume that these awards have different levels of recognition. For example, if social actors win Oscar, I expect that they can receive higher recognition than when they win different award. Hence, I can expect significant variations in the degree of change in film production teams' recognition when they receive awards from award-giving third parties that also have varying degrees of recognition. In Figure 1, I plot the proportions of films made with digital cinema cameras that received at least one award from 2000 to 2010. Although the proportions changed from 0.7% in 2000 to 7.2% in 2010, adoption of this innovation did not automatically guarantee an award.

===== Figure 1 is about here=====

In this study, I assume that the cinematographer and the director, i.e. a film production team, can decide to select which camera, i.e. digital or analogue, they want to use in their movies.

**Variables**

*Dependent variables.*

To test hypothesis 1, I create a dummy variable to capture if a film production team adopts digital cinema cameras at time t.

For hypothesis 2, I create a dummy variable to capture if a film production team adopts digital cinema cameras at time t in specific genres such as Comedy, Crime, Family, Romance, History, and Drama. In the sample period, a film production team are less likely to use digital cinema cameras in these genres as Figure 2 suggests. This means that adopting digital cinema cameras can be riskier in these genres. To capture this, I create this dependent variable.

===== Figure 2 is about here=====

*Independent variables.*

*Recognition.* To capture the level of recognition, I collected all award data for cinematographers and directors from 1994 to 2010. Then I computed the recognition of each award by using the Page Rank measure with the "page.rank" command in the R package.

The Page Rank is a measure of network centrality developed for the Google search engine. The idea is that a website's centrality increases if it is linked to many other websites that are also linked to many other websites (Page, 1997). This idea of centrality corresponds to my idea of different levels of recognition between awards and sequential patterns of receiving awards in this industry. I assume that a higher recognition award is connected to many other awards and social actors need to make an effort to receive higher recognized award. To compute this, I constructed directional network matrices that capture how award i has higher level of recognition compared to award j. A cell (i. j) represents the number of actors who receive award j at time t–1 and received award i at time t–5 to t–2, where t is the year. By tracking this, I try to capture smaller number of people who receive highly recognized/highly centralized award while more people receive less recognized/centralized awards. The Page Rank scores range from 0 to 1. The scores increase when awards are more central in the directional networks.

After I compute the Page Rank score, I realized that this score does not capture that receiving Oscar is the highest level of recognition. In Hollywood movie industry, winning Oscar (also known as Academy Award) gives highest recognition to award receivers in their career (Baumann, 2001). To capture this, it is more reasonable to weight the calculated Page Rank scores with proximity of an award to the Academy Awards. To do so, I considered the number of steps or geodesic distances required for an award to reach the Academy Award in the aforementioned directional matrices. I set the score of the Academy Awards at 1 and computed each award's geodesic distance to the Academy Awards in the directional matrices with UCINET. I then weighted each award's Page Rank by multiplying it by 1 / $\sqrt{}$(1+geodesic distance to the Academy Awards). If an award has a higher Page Rank and a shorter distance to the Academy in the directional matrices, its score is closer to 1.

After measuring this, I assign recognition scores to those who received awards. Some social actors do not produce movies nor receive awards every year while others might actively produce movies and have more chances to receive many awards in a year. To adjust this, I take an average of recognition score last three years. Then, I take the difference of these scores from time t-1 to t (*Recognition loss (continuous)*). I also code a dummy variable as 1 if the recognition that the member received in the previous 3 years fell by at least 3 percent from time t–2 to t–1 (*Recognition loss (dummy)*). The threshold of 3 percent might be arbitrary. Thus, I use alternative thresholds such as 5 precent, 10 percent, and 20 percent in the main analysis.

*Control Variables.*

I include several control variables that can influence the adoption of digital cinema cameras. First, limited film budgets might promote the adoption of digital cinema cameras, I include the logarithms of films' budgets. In case of missing data, I used the population average budget. Second, I control for film running times. Film production teams might be more interested in digital cinema cameras for longer films. This is because digital cinema cameras do not require frequent reloads of film and save costs in film development. Third, I control for the peculiar signaling effects of the Academy Awards (Jensen & Kim, 2015) by counting the number of members in a film production team who received Awards after 1994. Fourth, I control for potential effects caused by differences in film distribution companies and included dummy variables for five major companies, including Fox, MGM, Paramount, Sony, and Warner Brothers. Fifth, because films in some specific genres, such as science fiction (SF), might be more appropriate for digital technologies, I included dummy variables that indicate a film's genre in terms of adventure, fantasy, horror, thriller, and SF. Sixth, in order to control for experiences of past work, I include the tenure of the film production member. Finally, in order to control for time effects, I included year-dummy variables.

**Analytic approach**

Hypotheses 1 and 2 use logistic regressions for all samples in the dataset because the dependent variable is the dummy representing digital cinema camera adoption. In this research, I consider decision on digital cinema camera by cinematographer and director in a movie. As there are cases in which the same team members worked together in more than one film, I use the cluster option to allow for correlations between observations.

## RESULTS

Table 1 shows the summary statistics. Table 1 shows that the average of budget (ln) is 17.27. Average of tenure of a film production team is 17.8 years. The number of movies that a cinematographer and director worked together is on average 1.2 movies.

===== Table 1 is about here=====

Table 2 shows the results of t-test that I conduct to see if digital cinema camera adopters can improve their recognition and financial performance. Even though they adopt new technology, if their recognition or financial performance such as box office and opening box office are the same, their risky behavior does not give any benefits to them. To check this, I examine the t-test. I can find there are differences between digital cinema camera adopters and non-camera adopters in terms of recognition and financial performance. Especially, digital cinema camera adopters can increase their recognition compared to non-adopters.

===== Table 2 is about here=====

Table 3 shows the regression results of logit analysis for adoption of digital camera. When a film production team receive less recognition 3% ($\beta = 0.6028$, $p < 0.10$), 5% ($\beta = 0.4448$, $p < 0.10$), and 10% ($\beta = 0.6818$, $p < 0.05$), the results illustrate that they are more likely to adopt digital cinema camera. From this table, I can also interpret that social actors who drops their recognition more, they are more likely to adopt digital cinema camera. This is consistent with what I expected in Hypothesis 1. Hence, Hypothesis 1 receives supports.

===== Table 3 is about here=====

Table 4 shows the additional analysis for Hypothesis 1. I use the continuous variable for measuring the recognition loss. Model 1 represents linear model while Model 2 shows the results of logit analysis. I can interpret that social actors will adopt digital cinema camera by 0.3171 as they decrease 1 unit of their recognition ($p < 0.10$). Model 2 provides the consistent result as Model 1 ($\beta = 3.0158$, $p < 0.10$). In this table, I only include samples that social actors experience recognition loss. Therefore, compared to previous table, the number of observations is fewer.

===== Table 4 is about here=====

Table 5 represents the regression results of logit analysis for adoption of digital cinema camera in riskier genres. I consider the cases that social actors drop their recognition 3%, 5%, 10%, and 20% compared to their previous recognition. I cannot find significant results in Model 1 to Model 3. In Model 4, I find that social actors who drop their recognition more than 20% will adopt digital cinema camera in riskier genres. This is consistent with what performance feedback theory suggests i.e. the differences between their aspirations and their performance is greater, social actors take risks. Hence, Hypothesis 2 is supported. In Model 5, I consider continuous variable of recognition loss, which captures how much social actors reduce their recognition compared to their previous year. Model 5 shows that social actors who drop their recognition more, they are more likely to adopt digital cinema camera. Model 5 has fewer observations compared to Model 1, 2, 3 and 4. This is because I only include social actors who experience recognition loss and exclude the cases they do not change their recognition and receive more recognition. However, still the result is marginally significant ($\beta$= 2.9021, $p < 0.10$).

===== Table 5 is about here=====

# DISCUSSION

In this study, I examine how social actors who receive less recognition adopt new digital cinema camera. By referring to performance-feedback theory, I argue that social actors interpret their recognition loss as failure, to improve their situation, they are more likely to take risky decision i.e. adopt new technology. Especially, those who drop their recognition significantly show their riskier behavior.

## Contributions

First, this study can advance the literature on role of different awards by considering how social actors who receive less recognition improve their recognition by observing digital cinema camera adoption. Previous research has shown that different awards can effectively signal to consumers and influence financial performance (Gemser et al., 2008). This study follows the similar assumption that each award provides different levels of recognition to award receivers, but it focuses on how these social actors change their situation to improve their recognition.

Second, to capture different levels of recognition, this study refers to the social network analysis. By using all awards data and Page Rank package in R, I calculate the level of recognition of each award. Previous studies on social network research has focused on non-human network such as blog, website, and movie similarity to investigate how these networks can garner attention of consumers. I believe this study can contribute to this stream of studies.

Third, this study can advance the performance-feedback theory by considering non-financial performance as aspirations of social actors. Recently, research has increased focus on non-financial performance measures such as status (Baum et al., 2005), safety (Baum & Dahlin, 2007), organization size (Greve, 2008), and product quality (Parker et al., 2017). Recognition can provide benefits to social actors and can be related to their performance, so it is crucial for them to manage it. Hence, focusing on recognition as non-financial performance measure can advance our understanding of performance-feedback theory.

**Limitations**

There are several limitations in this study. First, to improve their recognition, I consider new technology adoption from analogue camera to digital one. I believe this transformation has significant impact on film making procedure and way of artistic expression. However, to recover their recognition, film production team can change the working collaborators or content of their work. Future research can consider this.

Second, I did not classify types of awards when I develop award-based network. Some awards are critic-based, consumer-based, and peer-based. I believe network of awards can capture the different level of recognition. However, many research have considered the characteristics of difference types of awards (Cattani et al., 2014; Gemser et al., 2008).

Third, I just include films produced by main production companies in my sample. Even though I controlled the budget of the movies, by selecting main production companies, I thought I can control this in a cleaner way. Budget is also related to camera selection. It is important for me to control this factor. However, such as the movie "Leaving Las Vegas" released in 1995, even though the production company is not mainstream one, the director of the film receives Oscar nomination. My sample can miss this kind of sample.

Even though I have several limitations, I believe this research can provide insightful ideas and advance previous literature on recognition, networks, and performance-feedback theory.

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**Table 1.** Summary Statistics

| | Mean | S.D. | Max | Min | p25 | p50 | p75 |
|---|---|---|---|---|---|---|---|
| Digital camera adoption | .0768137 | .2663903 | 1 | 0 | 0 | 0 | 0 |
| Recognition loss (3%) | .2019915 | .4016287 | 1 | 0 | 0 | 0 | 0 |
| Past Oscar nominations | .059744 | .3122431 | 4 | 0 | 0 | 0 | 0 |
| Budget (ln) | 17.27341 | 1.080812 | 19.51929 | 9.615806 | 16.70588 | 17.37086 | 17.9899 |
| Tenure of film production team (mean) | 17.79751 | 7.935735 | 49.5 | 0 | 12 | 17 | 23 |
| Number of movies that a film production team worked together | 1.214083 | .624848 | 7 | 1 | 1 | 1 | 1 |
| DreamWorks | .0540541 | .2262048 | 1 | 0 | 0 | 0 | 0 |
| Fox | .1792319 | .3827542 | 1 | 0 | 0 | 0 | 0 |
| MGM | .0227596 | .1491893 | 1 | 0 | 0 | 0 | 0 |
| Paramount | .1084637 | .3107897 | 1 | 0 | 0 | 0 | 0 |
| Sony | .1618065 | .3681627 | 1 | 0 | 0 | 0 | 0 |
| Universal | .1785206 | .3821566 | 1 | 0 | 0 | 0 | 0 |
| Warner Brothers | .2642248 | .4408747 | 1 | 0 | 0 | 0 | 1 |
| Walt Disney | .0967283 | .2950903 | 1 | 0 | 0 | 0 | 0 |
| Action | .242532 | .427936 | 1 | 0 | 0 | 0 | 0 |
| Adventure | .1806543 | .3839426 | 1 | 0 | 0 | 0 | 0 |
| Fantasy | .1180654 | .3228004 | 1 | 0 | 0 | 0 | 0 |
| Horror | .0775249 | .2668517 | 1 | 0 | 0 | 0 | 0 |
| Science Fiction | .1056188 | .3065891 | 1 | 0 | 0 | 0 | 0 |
| Thriller | .3165007 | .4641275 | 1 | 0 | 0 | 0 | 1 |

**Table 2.** The results of ttest about rewards by digital cinema camera adopters

| | Diff. | Std. Error | Obs. |
|---|---|---|---|
| Recognition | 0.0336** | 0.0129 | 1406 |

| | Diff. | Std. Error | Obs. |
|---|---|---|---|
| Box Office | -2.8918e+07*** | 10044073.2145 | 1306 |

| | Diff. | Std. Error | Obs. |
|---|---|---|---|
| Opening Week Box Office | -6679221.6035*** | 2342999.0204 | 1301 |

Difference is between mean of non-digital camera adopters and that of digital camera adopters.

**Table 3.** Regression results of Logit analysis for adoption of digital camera

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Recognition loss (3%, dummy) | 0.6028* | | |
| | (0.3268) | | |
| Recognition loss (5%, dummy) | | 0.4448* | |
| | | (0.2673) | |
| Recognition loss (10%, dummy) | | | 0.6818** |
| | | | (0.3331) |
| Action | 0.6306* | 0.6040* | 0.6303* |
| | (0.3496) | (0.3456) | (0.3511) |
| Adventure | -0.0741 | -0.0610 | -0.0725 |
| | (0.3761) | (0.3722) | (0.3775) |
| Fantasy | 0.5172 | 0.5089 | 0.5185 |
| | (0.4331) | (0.4284) | (0.4338) |
| Horror | -0.6509 | -0.6287 | -0.6601 |
| | (0.6618) | (0.6573) | (0.6619) |
| Science Fiction | 0.7699* | 0.7620* | 0.7753* |
| | (0.4120) | (0.4084) | (0.4127) |
| Thriller | 0.5034 | 0.4984 | 0.5103 |
| | (0.3792) | (0.3759) | (0.3797) |
| Past Oscar nominations | 0.7204* | 0.7176* | 0.7307* |
| | (0.3974) | (0.3927) | (0.3973) |
| Budget (ln) | -0.2041 | -0.1978 | -0.2050 |
| | (0.1999) | (0.1983) | (0.2002) |
| Tenure of film production team | -0.0032 | -0.0028 | -0.0034 |
| | (0.0188) | (0.0186) | (0.0189) |
| Number of movies that a film production team worked together | 0.1230 | 0.1247 | 0.1183 |
| | (0.1646) | (0.1641) | (0.1649) |
| Constant | -2.4392 | -2.4660 | -2.4273 |
| | (3.1109) | (3.0895) | (3.1122) |
| Production company dummy | Yes | Yes | Yes |
| Year dummy | Yes | Yes | Yes |
| Observations | 1180 | 1180 | 1180 |
| Log lik. | -267.7045 | -268.1873 | -267.2820 |
| Chi-squared | 47.8152 | 48.6766 | 48.6162 |

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, Standard errors are clustered at cinematographer-director level.

**Table 4.** Additional results of linear model and logit model for adoption of digital camera

| | Model 1 Linear model | Model 2 Logit model |
|---|---|---|
| Recognition loss (continuous) | 0.3171$^{*}$ | 3.0158$^{*}$ |
| | (0.1866) | (1.7437) |
| Action | 0.0142 | 0.1829 |
| | (0.0545) | (0.7913) |
| Adventure | -0.0851 | -1.3637 |
| | (0.0536) | (0.9365) |
| Fantasy | 0.1593$^{**}$ | 1.4362$^{**}$ |
| | (0.0795) | (0.7123) |
| Horror | 0.0295 | 0.6221 |
| | (0.0650) | (0.8872) |
| Science Fiction | -0.0131 | -0.1986 |
| | (0.0560) | (0.8960) |
| Thriller | 0.0104 | -0.0947 |
| | (0.0416) | (0.6925) |
| Past Oscar nominations | 0.0120 | -0.4060 |
| | (0.0535) | (1.2151) |
| Budget (ln) | 0.0284 | 0.6937 |
| | (0.0200) | (0.5782) |
| Tenure of film production team | -0.0016 | -0.0214 |
| | (0.0026) | (0.0369) |
| Number of movies that a film production team worked together | -0.0173 | -0.2870 |
| | (0.0295) | (0.2752) |
| Constant | -0.4709 | -16.8992 |
| | (0.3285) | (10.6323) |
| Production company dummies | Yes | Yes |
| Year dummies | Yes | Yes |
| Observations | 244 | 168 |
| Log likelihood | -19.9845 | -51.3426 |
| Chi-squared | | 50.0363 |

Robust standard errors in parentheses, $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$, Standard errors are clustered at cinematographer-director level.

**Table 5.** Regression results of Logit analysis for adoption of digital camera in risky genres

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Recognition loss (3%, dummy) | 0.4149 | | | | |
| | (0.2996) | | | | |
| Recognition loss (5%, dummy) | | 0.3312 | | | |
| | | (0.2552) | | | |
| Recognition loss (10%, dummy) | | | 0.4663 | | |
| | | | (0.3012) | | |
| Recognition loss (20%, dummy) | | | | 0.5021* | |
| | | | | (0.3005) | |
| Recognition loss (continuous) | | | | | 2.9021* |
| | | | | | (1.6737) |
| Past Oscar nominations | 0.4354 | 0.4376 | 0.4385 | 0.4355 | -1.2902 |
| | (0.4014) | (0.4009) | (0.4011) | (0.4018) | (1.0754) |
| Budget (ln) | -0.1098 | -0.1091 | -0.1091 | -0.1084 | 0.3577 |
| | (0.1437) | (0.1437) | (0.1435) | (0.1436) | (0.3948) |
| Tenure of film production team | 0.0029 | 0.0031 | 0.0027 | 0.0028 | -0.0239 |
| | (0.0162) | (0.0162) | (0.0162) | (0.0162) | (0.0410) |
| Number of movies that a film production team worked together | 0.0486 | 0.0495 | 0.0459 | 0.0448 | |
| | (0.1704) | (0.1720) | (0.1702) | (0.1698) | |
| Constant | -3.8368 | -3.8362 | -3.8560 | -3.8698 | -11.8856 |
| | (2.7164) | (2.7151) | (2.7127) | (2.7127) | (7.2510) |
| Production company dummies | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Observations | 1180 | 1180 | 1180 | 1180 | 168 |
| Log likelihood | -226.3482 | -226.5250 | -226.1201 | -225.9438 | -45.5145 |
| Chi-squared | 90.4848 | 90.0405 | 90.8303 | 91.4206 | 28.0770 |

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, Standard errors are clustered at cinematographer-director level.

***Figure 1.*** *Proportion of Digital Cinema Camera Adoption from 2000 to 2010*

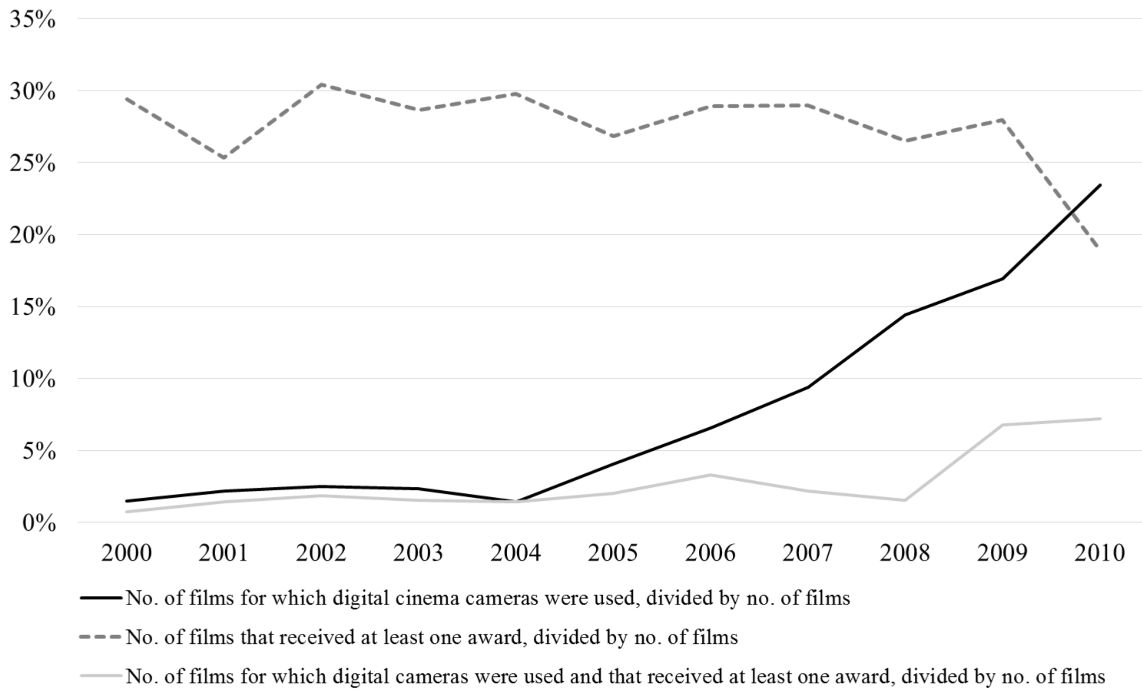

***Figure 2.*** *The ratio of adoption of digital cinema camera in each genre over years*