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Is There a Closure Penalty?
Cohesive Network Structures, Diversity, and Gender Inequalities in Career Advancement

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Abstract

That social capital matters is an established fact in the social sciences. How different forms of social capital affect gender disadvantages in career advancement is less clear, however. Qualitative research suggests that women face disadvantages in project-based labor markets where recruitment practices are based on informal and personal networks. Focusing on a project-based type of labor market, namely the U.S. film industry, this study argues that women suffer from social closure and face severe career disadvantages when collaborating in cohesive teams. At the same time, gender disadvantages are reduced for women who build social capital in open networks with a higher degree of diversity and information flow. I test and demonstrate these assumptions using a large-scale longitudinal dataset containing full career profiles of more than 1.2 million performances by 101,090 film actors in 483,949 feature film productions between the years 1900–2010. In particular, I analyze career survival models and interaction effects between gender and different measures of social capital and information openness. The findings reveal that female actors have a higher risk of career failure than their male colleagues when affiliated in cohesive networks, but have better survival chances when embedded in open and diverse structures. This study contributes to the understanding of how and what type of social capital can be either a beneficial resource for otherwise disadvantaged groups or a constraining mechanism that intensifies gender differences in career advancement.

Zusammenfassung

Sozialkapital stellt insbesondere auf projektorientierten Arbeitsmärkten eine wichtige Erfolgsressource dar. Auf die Frage, wie verschiedene Formen der sozialen Einbettung auf geschlechtsspezifische Erfolgsungleichheiten wirken, gibt es jedoch bislang keine eindeutige Antwort. Bisherige Einzelfalluntersuchungen legen nahe, dass Frauen besonders dann benachteiligt sind, wenn Rekrutierungspraktiken in hohem Maße auf informellen und auf persönlichen Netzwerken beruhen. Am Beispiel eines projektorientierten und durch informelle Rekrutierung gekennzeichneten „Winner-take-all"-Arbeitsmarktes – der US-Filmbranche – wird argumentiert, dass Frauen besonders dann Benachteiligungen erfahren, wenn sie ihre Karriere häufiger in engmaschigen, stark kohäsiven Teams aufbauen. Dagegen können sie Benachteiligungen deutlich reduzieren, wenn sie sich häufiger in Projektteams bewegen, die sich durch offene Netzwerkstrukturen und breite Erfahrungshintergründe auszeichnen. Auf Basis von Ereignisdatenanalysen und der Untersuchung vollständiger Karriereprofile von 101.090 US-Filmschauspielern in 483.949 Spielfilmproduktionen mit mehr als 1,2 Millionen Engagements testet der Beitrag diese Argumentation und zeigt – anhand diverser Indikatoren zur Messung von Teamkohäsion, Kollaborationshäufigkeit, Informationszugang und -vielfalt –, dass kohäsive Netze geschlechtsspezifische Karriereungleichheiten verstärken, während offene Netzwerke Benachteiligungen deutlich reduzieren. Vermutlich sind der in diesen Netzen höhere Informationsfluss und vor allem die Diversität der geteilten Informationen entscheidende Faktoren, die geschlechtstypische Benachteiligungen aufheben können. Diese Studie erweitert das Verständnis darüber, wie und unter welchen Bedingungen Sozialkapital zu einer vorteilhaften Ressource für benachteiligte Gruppen wird, und wann es beschränkende, Benachteiligungen intensivierende Wirkungen entfaltet.

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1 Introduction

Social capital has been an important concept and explanatory variable for a number of issues in the social sciences. Especially in economic sociology and organization studies, a burgeoning literature explains a wide range of outcomes using this concept (for an overview, see Adler/Kwon 2002). A central finding is that social capital has a functional dimension for labor markets: it reduces information and search costs, matches supply with demand, and positively affects individual career advancement. Specifically, it helps in acquiring new jobs, establishing future collaborations, and creating teams (Burt 1992; Gabbay/Zuckerman 1998; Schwab/Miner 2008; Podolny/Baron 1997; Giuffre 1999; Accominotti 2009; Granovetter [1974]1995). Social capital facilitates the share and transfer of knowledge within teams and among co-workers (Reagans/McEvily 2003; Inkpen/Tsang 2005; Tortoriello/Reagans/McEvily 2012; Wei/Zheng/Zhang 2011), hastens the diffusion and creation of innovations (Cuevas-Rodríguez/Cabello-Medina/Carmona-Lavado 2013; Tsai/Ghoshal 1998; Rost 2011; Rogers 2003; Obstfeld 2005) and enhances the productivity of teams (Reagans/Zuckerman 2001). Moreover, social capital affects team success and performance even in highly competitive, creative, and uncertain environments, such as video game production, musicals, professional soccer, or film production (Ferriani/Cattani/Baden-Fuller 2009; Grund 2012; Uzzi/Spiro 2005; Vaan/Vedres/Stark 2011; Balkundi/Harrison 2006).

Especially in project-based labor markets such as film, where recruitment practices are greatly dependent on interpersonal networks (Mathieu/Stjerne 2012; Ebbers/Wijnberg 2010; Blair 2001, 2003; Andersen 2013; Bielby/Bielby 1999; Delmestri/Montanari/Usai 2005; Jones 1996; Schwab/Miner 2008; Cattani/Ferriani 2008; Eikhof/Haunschild 2006; Eikhof/Haunschild 2007), social capital is highly important for getting jobs and structuring the market. While much of the literature on social capital highlights its positive and functional aspects, there is a dysfunctional, "dark" side (Gargiulo/Benassi 1999): social closure. If recruitment is mainly a result of interpersonal network embeddedness, there is a tendency to exclude and discriminate actors, an exclusion based on ascriptive characteristics that disregards talent (Tilly 1998; Bourdieu 1984, 1985; Lin 1999; DiMaggio/Garip 2012; Lin 2000). Qualitative research suggests that particularly women suffer from labor markets structured by informal recruitment practices, because men are more able to join important cohesive groups and get more return from their social capital investments (Grugulis/Stoyanova 2012; Roscigno/Garcia/Bobbitt-Zeher 2007;

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Christopherson 2009). Working in the creative industries means that actors have to network actively and extensively (Blair 2009): many jobs are negotiated through interpersonal networks, often in the evenings over a beer. Especially when women have to raise children, they are at a particular disadvantage because men can allocate more time than can women to building such career-relevant network relationships. In addition, when teams are dominated by male gatekeepers, this research suggests that women have fewer chances than men to acquire new jobs, because job-relevant information tends to flow through gender-specific homogenous networks.

However, research has still not systematically investigated whether and in what direction social capital and network structures affect women's chances to advance their careers. That gender inequalities persist in project-based labor markets is a well-studied fact (Bielby/Bielby 1992, 1996; Lincoln/Allen 2004; Lutter 2012a), but it is less clear how different forms of social capital affect these disadvantages to women. So far, insight has come from knowledge generated by in-depth interviews and case-study research. As of now, no quantitative account explains how the exposure to different types of network structures affects gender disadvantages in careers. For instance, Petersen et al. (2000: 772–773) review the empirical literature on networks and gender segregation and conclude that systematic knowledge is still very limited. They quote Granovetter, who notes in his review that this research gap is precisely the one "most in need of filling" (Granovetter [1974]1995: 177).

This article attempts to fill this gap. Drawing on social closure theory, I argue that gender inequality is particularly striking when actors are exposed to cohesive project teams during their career, while gender inequality is less severe when actors are involved in weaker, diverse network structures that allow for different forms of information flow and variance. Using a unique panel dataset which includes full career profiles of more than 1.2 million performances by 101,090 film actors in the US feature-film industry and advanced measures of network embeddedness, the study sheds light on the long-discussed but never quantitatively analyzed assumption that women are more likely to suffer from social closure. By analyzing interaction effects between gender and different measures of cohesion, social capital, and information diversity, the study finds that women face significant disadvantages during their career when they are affiliated more often with cohesive networks, a finding that is controlled for human capital and other success-related factors. Moreover, gender disadvantages are reduced substantially in careers featuring collaborations with less cohesive relations, weaker ties, and greater information diversity. If women engage in teams with greater genre and information diversity, the study finds they can reduce their risk of career failure to a level indistinguishable from that of men's. Gender disadvantages are then fully negated.

2 Social capital and gender: Theory and hypotheses

The number and quality of relationships – such as colleagues or collaborations, friends or family – can be subsumed under the notion of social capital if this social structure in any way forms an asset or resource (Burt 1992: 9; Baker 1990: 619). The strength of personal ties is usually conceptualized by the amount or frequency of contact, emotional affection, reciprocal behavior or trustworthiness (Granovetter 1973). Network structures can in different ways create social capital, either through strong, dense, and cohesive ties, or through network ties that are less cohesive, weaker, and more loosely connected (Burt 2000).

The classical approach comes from Coleman and highlights the assumption that strong ties or cohesive network structures form a beneficiary resource of social capital (Coleman 1988, 1990). According to Coleman, actors with frequent relationships are more likely to develop trust, conjoint identification, and shared norms among themselves, which in turn lead to reciprocal, cooperative, and pro-social behavior. In cohesive networks where actors interact repeatedly, the incentive to cooperate is relatively high because cooperation enhances a person's chances to receive help the next time it is needed. Any favor an actor receives from a colleague imposes an obligation to reciprocate in the future. As a consequence, actors in frequent relationships invest more in social capital because they can expect a higher return from this investment, as opposed to weaker relationships or one-shot interactions.

Contrary to this positive view, Bourdieu's work on social capital (Bourdieu 1980, 1985) stresses the negative aspects: cohesion divides actors into insiders and outsiders, fosters discrimination and exclusion, and is likely to produce social closure (for an overview see Lin 1999: 483, Lin 2000). According to Bourdieu, members of a social group develop a specific habitus, which is socialized, shared, and maintained, often unconsciously. The habitus imparts the "feel for the game" (Blair 2009: 121), attaches members to the group, and makes membership visible. It creates distinctive features that signal belonging or exclusion (Bourdieu 1984). Closure mechanisms are especially prevalent in cohesive network structures because the specific habitus that develops within the group restricts outsiders from gaining access to the group. The group-specific habitus reduces the integration capacity of a cohesive group and perpetuates existing boundaries between groups. Hence, social closure is likely to reproduce social inequalities.

Bourdieu's critical approach is mirrored in the homophily principle from social network theory (McPherson/Smith-Lovin/Cook 2001). According to this principle, networks tend to share and associate with those holding similar socioeconomic status, attitudes, behavior, and norms. The stronger the cohesion of the network, the more similar the network. One source of similarity is the greater potential for social control in cohesive groups. Any behavior that deviates from the group norm can be sanctioned, which in turn increases the group's homogeneity. Sanctioning either prompts members

to alter their behavior, conform to what the group regards as legitimate, and thus reproduce habitus, or it causes non-conformist members to leave the group, if they are not excluded outright.

With regard to gender inequality, it can be argued that particularly women are in danger of being disadvantaged by cohesive network structures, especially when the gatekeepers in these networks are male. Indeed, as research shows, the main gatekeepers in the film industry, e.g. producers, directors, writers, and editors, are as much as 80 to 90 percent male (Christopherson 2009: 88; Levy 1989: 36; Bielby/Bielby 1996: 254). Ascriptive categories are likely to influence membership in these project networks (Tilly 1998; Reskin 2003; Kanter 1977). For instance, recent research suggests that job seekers in white/male networks receive more relevant job information than do those in minority/female networks. At the same time, white/male networks consist of higher status contacts (McDonald 2011). Research on race inequality shows that personal contacts of the same race significantly increase same-race matching at the workgroup level (Stainback 2008; Petersen/Saporta/Seidel 2000).

Segregated personal networks seem to reflect themselves in segregated workgroups. In turn, this gives some groups an advantage and puts other groups at a disadvantage. In fact, much of the effect of social capital on success in job-seeking is actually explained by the homophily principle and the tendency for similar groups to come together (Mouw 2003; Ruef/Aldrich/Carter 2003; Schwab/Miner 2008; Faulkner/Anderson 1987), which increases the likelihood that ascriptive rather than meritocratic characteristics influence the hiring process. In addition, woman with children are at a particular disadvantage when recruitment practices are heavily influenced by interpersonal networks (Grugulis/Stoyanova 2012). In a study using survey data, Munch et al. (1997) show that having a child significantly reduces the size of a women's network, whereas there is no effect on men's network size. Taking these factors together, gender-homophilous reproduction can result in severe cumulative gender disadvantages over a course of a career (Bielby/Bielby 1992, 1996).

Especially in project-based labor markets, where allocation and matching frequency is much higher than in traditional labor markets, gender-homophilous matching processes can generate processes of "allocative discrimination" (Petersen/Saporta 2004), resulting in "glass ceilings" (Powell/Butterfield 1994), "glass doors" (Fernandez/Abraham 2011), or "old boy networks" (Jann 2003). This would explain why the film and media industries are biased towards a white, male, and middle-class workforce. According to Grugulis and Stoyanova (2012: 9), the workforce resembles the cultural background of the gatekeepers, who are also predominantly male, white, and middle class. At the same time, white, male, middle-class people have better economic resources to survive and adapt to the precarious and uncertain working conditions in the creative industries. Following this discussion, I propose hypothesis *H1:*

H1: The greater the cohesion of a team's network, the more pronounced are gender disadvantages in career advancement.

Another approach on social capital assumes that actors in weak or loosely connected network structures develop and benefit from social capital. Referring to the famous "strength of weak ties" theorem (Granovetter 1973), weak ties are exposed to a broader range of diverse communities because they bridge what Burt (1992) has called "structural holes"– insular groups of cohesive and distant networks. Actors who maintain weak ties can benefit from a brokerage position because they control the information flowing between two groups. A weak tie therefore connects and bridges otherwise separated groups. The broker position benefits the broker by increasing his or her social status. More important, the position gives the broker access to different sorts of people, communities, and cultures. Therefore, weak ties offer a much broader exposure to information, which can be advantageous in building and making use of social capital (for empirical evidence, see: Giuffre 1999).

Both forms of embeddedness, weak and strong, can be seen as complementary because they both create relevant, albeit different forms of social capital (Rost 2011). On the one hand, less central nodes suffer from closure by being outsiders, yet weaker ties profit from the diversity and information variance of far-distant cultures. On the other hand, strong ties are penalized by less diversity but benefit from more reliable and trustworthy information that is shared in cohesive networks.

Cohesion is especially beneficial in project teams when actors have to rely on the cooperation of others in order to perform well or to receive important information that would otherwise be costly or impossible to access. Research shows that members in cohesive teams invest more time in sharing information (Reagans/McEvily 2003) and transfer tacit, complex, or secret knowledge more often (Hansen 1999). By contrast, people with weak ties share useful but less complex knowledge.

Sharing complex knowledge is important for team success because complex information is less obvious and produces competitive advantages for those who have access to it. Hence, trust and familiarity are important to produce successful outcomes. Research shows that this is true up to a certain threshold: too much familiarity is again detrimental for team success (Rost 2011; Vaan/Vedres/Stark 2011; Vedres/Stark 2010; Stark 2009; Gargiulo/Benassi 1999, 2000; Uzzi 1997). For instance, Uzzi and Spiro (2005) show that creativity and team performance increase with team density up to a certain point, after which their positive effect is reversed. Although creative teams need a certain degree of cohesion in order to facilitate trust, too much cohesion or over-embeddedness imposes creative restrictions on team members, which results in less innovative outcomes. In a study on R&D teams, Reagans and Zuckerman (2001) find evidence that the effect of density on team performance is strongest when the cohesive team is also heterogeneous.

Creative teams also need the disruptive and dissonant features that are brought in through weak tie brokers bridging structural holes or by newcomers with different genre backgrounds who bring in fresh perspectives and new ideas (Perretti/Negro 2007; Stark 2009; Vedres/Stark 2010; March 1991; Ferriani/Cattani/Baden-Fuller 2009; Cattani/Ferriani 2008). In light of these findings, I assume that women suffer from closure tendencies in cohesive networks, as proposed with hypothesis 1, but they can take advantage of weaker and more diverse networks. These structures make them less dependent on a few (mostly male) gatekeepers who decide whether or not they are to be included in the in-group. They can diversify their risks and assets to a much greater extent and can have access to wider pools of information, which should result in lower dropout rates for women and reduced gender differences on average. Hence, I propose that gender inequality is decreased if women are attached to more open and diverse team structures.

H2: Gender disadvantages decrease in network architectures that are more open with regard to the diversity of ties, information flow, and genre background.

3 Data and method

This study uses data from the Internet Movie Database, which is currently the most complete database on movies, film makers, and the film industry worldwide. At present, it contains information on approximately two million film and TV productions, as well as more than four million individuals (actors, producers, directors, cinematographers, writers, designers, etc.). The database has a relatively high degree of validity because users can report errors to an editorial team; actors, their representatives, or other people listed in the database can provide information as well. Several sociological studies have been published using this data and thus confirming its validity (Rossman/Esparza/Bonacich 2010; Hsu 2006; Hsu/Hannan/Koçak 2009; Zuckerman/Kim 2003; Zuckerman, et al. 2003).

From the raw data, which is provided by imdb.com for noncommercial usage, I generate career profiles of male and female actors by their performances in feature films. I include an individual's full career profile if he or she appeared at least once in a feature film produced in the United States. A career profile includes all of that person's engagements that were recorded in the database between the years 1900 and 2010. I only include performances in feature films and thereby exclude television productions, video-only movies, and pornographic movies. The final dataset contains a total of 1,237,700 engagements of 101,090 actors (of which 32,439 or 32 percent are female) in 483,949 film productions.

In a project-based labor market such as the film business, the most basic measure for career advancement is survival. As Faulkner and Anderson (1987) show for producers and directors in Hollywood, the majority drop out after one or two movie productions. Only a small fraction actually "survives" for more than two movies. Simply to stay in the business means to advance a successful career. Accordingly, I use event history methods in order to estimate factors that influence career survival (Cleves/Gould/Gutierrez 2004). In particular, I use Cox regression to estimate hazards for career failure, that is, the risk of dropping out of the business.

Career failure is a binary variable that takes the value 1 at an actor's last entry in the database – which constitutes an actor's last performance. Otherwise, it is zero. Since the timeframe of the study ends in 2010, I do not know whether a career continues after 2010. This points to the common problem of censoring in survival data (Cleves/Gould/Gutierrez 2004: 29–32). To handle this problem, I treat only those actors who have been inactive within the ten years prior to 2010 as having failed careers.[1] In other words, if an actor has not been involved in a production since 2000, I treat his or her last production as career failure = 1. If there is a record after 2000, I treat this career as ongoing, hence, career failure status = 0.

I fit Cox proportional hazard models (Cox 1972) because the literature suggests these as the most flexible instrument estimating survival data (Blossfeld/Rohwer 2002; Box-Steffensmeier/Jones 2004; Cleves/Gould/Gutierrez 2004). Previous tests of the proportionality assumption suggested that Cox modeling is appropriate. In order to surmount possible violations in the regression assumptions, such as error independence among observations, all estimations rely on robust standard errors clustered by actors (Lin/Wei 1989). I also present the results of a few alternative model specifications and sensitivity analyses, in order to test the robustness of the discussed findings.

Measurement of variables

Table 1 presents descriptive statistics for all variables used in this study. Hypothesis *H1* assumes that women face disadvantages when they work more often in cohesive team structures rather than in weaker structures. In order to measure the cohesion of a film production team, I follow De Vaan, Vedres, and Stark (2011: 13–14) and rely on their two related but distinct measures of social capital: interpersonal team familiarity and recurring cohesion. Interpersonal familiarity, developed by Newman (2001) in its core form, measures the intensity of prior relations between each pair of collaborators

1 I repeated the analysis using a less conservative timeframe of five years. The results did not differ from those presented below; these can be made available upon request.

within a film production team. It is constructed in the following way: in a dataset sorted by the release date of each film, the strength of collaboration between individual *i* and *j* (if any) is given by

$$w_{ij} = \sum_f \frac{\delta_i^f \delta_j^f}{n_f - 1}$$

where δ_i^f is 1 if *i* was part of film *f* and zero otherwise; likewise, δ_i^f equals 1 if individual *j* was part of film *f* and zero otherwise. If there has been any collaboration between *i* and *j* in any film production, then $\delta_i^f \delta_j^f$ will count as 1, and zero otherwise. n_f is the number of crew members in film *f*. By dividing by $n_f - 1$, I give collaborations in smaller productions a greater weight, assuming that members know each other better if they have worked together in crews of a smaller size as opposed to larger crews. w_{ij} then gives us a number of prior collaborations over all film productions for each pair of individuals in the dataset. I then calculate the sum of the off-diagonal, lower triangular values of w_{ij} for each film crew *c* in the dataset, and adjust it by crewsize n_c. Note that taking the lower triangle elements prevents the same collaboration being counted twice. The sum yields a measure of interpersonal *team familiarity:*

$$\textit{Team familiarity}_c = \frac{1}{n_c} \sum_{i>j} w_{ij}$$

Team familiarity conceptualizes social capital at the dyadic, person-to-person level. It measures the degree to which people in a current team know each other from past collaborations. It takes on the value 0 if no prior collaboration exists in a focal team. Higher positive values indicate a greater degree of prior collaborations among the members of a crew. Naturally, this variable includes both weak and strong ties: I do not know whether a prior collaboration reflects a strong or weak relationship. The only thing I know is that two people have been colleagues in the past. In order to better capture possible closure tendencies from cohesion, I follow De Vaan et al. (2011: 13–14) and calculate their measure of *recurring cohesion*. Recurring cohesion considers cliques of at least three persons who have repeatedly collaborated in past productions. For instance, if actors A, B, and C worked together in a movie and repeat their collaboration in a later production, this later production is considered more cohesive because a full clique rather than just a dyadic relationship reassembles itself in a new team. Recurring cohesion is calculated in the following way: for each film team in the dataset, I identify all cliques of three or more members who have collaborated in a prior film. Having identified q_c cliques ranging from clique $v = 1$ to q_c for each team *c*, I measure the overlap of individuals recurring in these cliques. This results in a non-symmetric $q_c \, x \, q_c$ matrix $\boldsymbol{L}^c$, in which each entry L^c_{vw} contains the number of persons appearing both in clique *v* and *w*, recorded as a share of the number of persons in clique *v*. If S_v is the number of individuals of the current film crew *c* in clique *v*, and S_c is the number of individuals in film crew *c*, then *recurring cohesion* is given by:

$$Recurring\ cohesion_c = \frac{\sum_{v \neq w} \left(1 + L_{vw}^c\right) \frac{S_v}{S_c}}{2\left(q_c - 1\right)}$$

The variable can be read as a team's average degree of cohesion, measured as the extent to which past cliques of at least three persons reassemble in the current production. The quantity takes on the value 0 if no cohesion exists, that is, no clique of recurring collaboration is present in the focal team; it takes a positive value if there is cohesion in a team. Higher values indicate a greater degree of recurring cliques.

The second hypothesis assumes that gender disadvantages become less severe in careers in which a person associates more often with teams structured by open and diverse networks. It is assumed that these networks facilitate the flow of information in a way that benefits otherwise disadvantaged groups. In order to test this, I rely on three measures of team openness and information diversity. The first is simply the *share of newcomers* within a film team *c*. I follow Perretti and Negro (2006) as well as (March 1991) and assume that the higher the percentage of newcomers within a team is, the more likely it will be that fresh ideas are bought into the production, as well as new perspectives, new combinations of relationships, and heterogeneous information pools.

The second diversity measure takes into account the individual exposure to different genre backgrounds. Each film in the database is described using a total of 28 genre dummies (for a list, see Table A2 in the appendix), the combination of which determines the genre of the film. For example, the Spielberg movie *E.T.* (1982) is described by the three genre dummies "adventure," "drama," and "family" and Zemeckis' *Back to the Future* (1985) as "adventure," "comedy," and "sci-fi." I calculate Hsu's (2006) measure of *niche width*, which is the total number of distinct genre categories that each film production addresses. In line with Hsu (2006) and Zuckerman et al. (2003), I assume that the broader an actor's identity and genre spanning, measured by this quantity, the greater is the likely exposure to diverse and different categories, genres, and information pools. If an actor has a broad genre portfolio by having worked in diverse film projects, I assume the actor has access to a broad source of information, diverse categories and genre cultures, and different schools of thought.

While this measure takes individual genre diversity into account, I also calculate a team-based genre-diversity measure. I assume that creative diversity, that is, the different genre backgrounds among the members in a film team, generates stylistic dissonance between different genre standards and the way cultural products are produced. This then creates an atmosphere of productive friction in which innovation and creative synergy within a team reaches an optimal level (Stark 2009). I assume that women can profit from this diversity because the exposure to various people with different cultural

genre backgrounds provides access to various sources of information and opens up beneficial opportunities in job searches – as opposed to uniform, homogenous film teams sharing basically the same artistic standards and the same channels of knowledge.

To measure the *genre diversity of a team*, I calculate the distance measure used by Rodan and Galunic (2004), Phelps (2010), and De Vaan et al. (2011), which is based on Jaffe's (1986: 986) well-known measure of proximity/dissimilarity. This distance measure calculates the stylistic distance between each team member of a focal team based on their genre backgrounds from past productions. In order to construct this measure, I first quantify each actor's genre history using the 28 distinct genre dummies. In doing this, I count the number of movies in each of the 28 genres in which an actor performed, up to each time point *t*. In a second step, I focus on the team level and calculate the sum of genre histories for all members of a focal film crew. I do this for all film teams in the dataset and for each of the 28 genres. This gives us a distribution showing the degree to which each genre *k* is represented within the experience background of the whole crew. I now calculate *K*-dimensional vectors $f_i = (f_{i1}, \ldots, f_{iK})$, where f_{ik} is the fraction of crew member *i*'s genre history in genre category *k*. Based on Jaffe (1986), the genre distance *d* between a team member *i* and *j* is derived by:

$$d_{ij} = 1 - \left(\frac{\sum_{k=1}^{K} f_{ik} f_{jk}}{\left(\sum_{k=1}^{K} f_{ik}^2 \right)^{\frac{1}{2}} \left(\sum_{k=1}^{K} f_{jk}^2 \right)^{\frac{1}{2}}} \right)$$

That is, d_{ij} is one minus the length of the projection of the normed vector f_i onto the normed vector f_j. f_i and f_j have only non-negative entries, hence, the distance measure can take values between 0, representing complete similarity in the genre backgrounds between members *i* and *j*, and value 1, which stands for the maximum possible dissimilarity in genre history between *i* and *j*. I then sum this index up for all members of a crew and adjust for team size. For each film crew *c*, this gives us a measure of *genre diversity*, which is defined as:

$$\textit{genre diversity}_c = \frac{1}{n_c} \sum_{i>j} d_{ij}$$

where d_{ij} is the genre distance measure of crew member *i* from *j*, and n_c the number of crew members of focal film crew *c*. Again, note that the measure takes the off-diagonal elements of the lower triangle of the distance matrix into account and adjusts for crew size.

Table 1 Descriptive statistics for all variables used in this study

Variable	Mean	Std. Dev.	Min	Max
Dependent variable				
Career failure	0.031649	0.175064	0	1
Career duration	12.1074	11.2007	0.002732	84.8333
Predictors				
Female	0.266401	0.442077	0	1
Age	40.6077	14.6657	3	86
Number of movies produced	40.9446	64.0755	1	1456
Cumulative number of awards	0.181304	1.40389	0	93
Cumulative billing position	155.626	211.884	0	11444
Number of roles not credited	18.1555	42.8473	0	1402
Origin USA	0.573848	0.494517	0	1
Origin UK	0.050935	0.219865	0	1
Origin Germany	0.021784	0.145978	0	1
Origin France	0.027591	0.163797	0	1
Origin Italy	0.021786	0.145983	0	1
Has been producer	0.19658	4.13839	0	1094
Has been director	0.789998	8.16801	0	619
Titles in English	30.8966	57.2004	0	1005
US productions	33.1733	63.542	0	1449
Major titles	38.7743	62.8823	0	1448
Sequels	1.13211	2.76291	0	287
Novels	5.08121	8.3098	0	140
Crew size	43.6656	43.6911	1	1311
Genre: Thriller/Crime	–0.002524	1.00716	–3.51662	4.95341
Genre: Family/Adventure/Comedy	0.040625	1.02102	–1.64034	8.49889
Genre: Action/Adventure/Western	0.009935	1.04174	–3.36408	11.3632
Genre: Drama/Romance/History	0.215343	0.965018	–7.69608	3.73876
Person per movie ratio	13.1297	5.23889	0.554348	22.8402
Team familiarity	0.170715	1.07764	0	73.0201
Recurring cohesion	2.34127	6.70374	0	310.24
Share of newcomers	0.175633	0.179326	0	1
Niche width	2.08138	1.09393	0	10
Genre diversity	0.306902	0.054462	0	0.42085

Note: N = 1,237,700 actor-film observations.

Control variables

I control for a number of variables at the film- and person-specific level that should have an effect on career survival chances. *Age (in years):* this variable is calculated from the birth year information in the database. I assume that the hazard rate for career failure increases with age. *Number of movies produced:* this is a human capital variable reflecting job experience, as measured by the number of movies with which an actor had been associated by time point *t*. Greater job experience should decrease the risk of career failure. *Cumulative number of awards:* this variable measures star power or cumulative advantages in the sense of DiPrete and Eirich (2006). In constructing this variable, I record all award nominations and winnings an actor received personally (best

male or female actor, best supporting role, etc.) for a film production at an important film festival. I use awards data from the 44 most important film festivals worldwide (for a detailed list, see Table A2), including the fourteen most important US film awards, all fourteen international "A" film festivals, and another sixteen "B" film festivals.[2] *Cumulative billing position:* this variable represents the ranking position occupied by an actor within the credits of a production. The billing position is available in the database for each film production that offers a competitive role ranking. The lower this number, the better the position: billing position number 1 represents the leading role, position 2 the second leading role, position 3 the main supporting role, and so on. Usually, the ranking is a competitive part of the contract and reflects an actor's star power or ability to negotiate a starring role within a production. A better ranking is usually associated with greater visibility, pay, and audience recognition, and should therefore positively affect an actor's reputation and ability to acquire future engagements. I accumulate this variable over all engagements in order to reflect past experiences and leading roles that might still affect future engagements. *Number of roles not credited:* not all roles within a production are ranked by the billing position. Roles below the top-10 or top-20 cast are often not listed in the credits. This variable records the cumulative number of movies an actor was engaged in without having a credited role. Career survival chances should be higher if this variable is lower on average. *Origin:* I include five dummy variables to control for an actor's country of origin. The five dummies reflect the most frequent birthplaces in the database, which is the United States, the United Kingdom, France, Germany, and Italy. All remaining birthplaces act as the reference category. *Has been producer/director:* actors also work as directors or producers, which normally demonstrates a stronger and stable career position (Baker/Faulkner 1991). I include two measures that count the cumulative number of movies at time point t in which an actor has worked as a producer or director, respectively. *Titles in English:* this variable is the number of English-language productions an actor appeared in. Potential audiences and box office returns are much larger if a movie has been produced in English or has been translated into the English language. Especially for actors who are not native English speakers, this signals a higher visibility and a higher likelihood to sustain a career. *US productions:* this variable sums up the number of US-produced movies an actor appeared in. Similar to the previous variable, this one reflects international visibility since most American productions are marketed worldwide. *Major titles:* this variable is the number of major movie productions in which an actor performed. Contrary to independent movies, major productions have a higher budget, a greater number of theater screenings, and eventually, more box office returns. *Sequels:* this measure represents the cumulative number of productions in a sequel in which an actor appeared. Sequels (for example, *Rocky III*) often attract large audiences and return much higher profits than non-sequels. *Novels:* similarly, productions based on a novel often yield higher return rates. This measure represents the number of times an actor appeared in films with a novel-based script. *Crew size*: this figure shows the number of crew members

2 An encyclopedic overview on movie awards is given by Gebert (1996) and O'Neil (2001). See Gemser et al. (2008) for an analysis on how these awards signal quality.

for each engagement and thus represents a proxy for the movie budget (for a similar approach see: Rossman/Esparza/Bonacich 2010: 40), since costly productions usually have larger crews. *Genre factor variables:* to control for possible genre effects, four variables – *Thriller/Crime; Family/Adventure/Comedy; Action/Adventure/Western; Drama/Romance/History* – represent the factor scores from a principal component analysis on the 28 genre dummies that classify every film production in the dataset. Table A1 in the appendix displays the varimax-rotated solution of the factor analysis. *Person per movie ratio:* this variable reflects the opportunity structure for each actor in the business. If a higher number of actors compete for a fewer number of available jobs in a particular year, I assume that the hazard rates of career failure are increased. The variable is defined as the total number of actors in a given year, divided by the total number of movies released in that year.

4 Results

Table 2 presents the results of a set of nested model estimations. For all metric variables, I use logged values to control for skewness and to account for diminishing marginal returns of success.[3] I begin with a baseline model in which I enter the female dummy and all control variables (Model 1). As can be seen from Model 1, female artists have a circa 10-percent higher risk of failure than their male colleagues. The effect remains robust across all model specifications. Controlling for all other factors in the model, I find that women drop out of the business much earlier than men.

The remaining controls are all in line with the expectations. Age has a significant positive effect. The risk of failure increases with seniority. At the same time, job experience lowers the risk of ending a career. The same holds true for number of awards: the more awards an actor receives, the more the risk for career failure is reduced. In the same way, having a portfolio of higher ranked billing positions increases career survival time. Cumulative advantages, or Matthew effects (Merton 1968; DiPrete/Eirich 2006), seem to be a critical factor for survival in the film business. Similarly, actors who have worked as a producer or director also increase their career chances, although the director effect is not a robust effect across all models. Appearing in international English-language productions, having a major distributor, and being part in a sequel are further factors that greatly increase survival chances. However, productions based on novels decrease the chances to survive. The same holds true for actors appearing in US productions – as compared with actors working in other countries. Actors based in the United States have lesser chances for survival because the US business is probably more competitive than film industries in other countries. The effects of the origin variables point in the

3 For all variables that have a zero value, I add the constant 1 to the variable in order to enable taking the natural logarithm.

Table 2 Main results: Cox regressions on career failure hazards

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	0.097***	0.091***	0.092***	0.092***	0.043**	0.604***
	(8.657)	(8.124)	(8.169)	(8.165)	(3.018)	(6.138)
Age (ln)	0.120***	0.128***	0.126***	0.128***	0.128***	0.128***
	(7.317)	(7.836)	(7.674)	(7.800)	(7.810)	(7.784)
Number of movies produced (ln)	–0.213***	–0.224***	–0.203***	–0.217***	–0.219***	–0.225***
	(–9.456)	(–9.957)	(–9.028)	(–9.637)	(–9.741)	(–9.992)
Cumulative number of awards (ln)	–1.011***	–0.986***	–0.993***	–0.979***	–0.978***	–0.979***
	(–24.025)	(–23.565)	(–23.668)	(–23.414)	(–23.368)	(–23.338)
Cumulative billing position (ln)	0.055***	0.069***	0.068***	0.075***	0.075***	0.076***
	(11.058)	(13.675)	(13.602)	(14.822)	(14.978)	(15.087)
Number of roles not credited (ln)	0.165***	0.139***	0.153***	0.137***	0.140***	0.143***
	(15.957)	(13.473)	(14.911)	(13.263)	(13.584)	(13.809)
Origin USA	0.024+	0.034*	0.033*	0.038**	0.037**	0.036**
	(1.774)	(2.559)	(2.522)	(2.890)	(2.799)	(2.700)
Origin UK	0.159***	0.157***	0.158***	0.161***	0.159***	0.157***
	(6.743)	(6.598)	(6.702)	(6.767)	(6.704)	(6.608)
Origin Germany	–0.059	–0.047	–0.049	–0.041	–0.041	–0.040
	(–1.468)	(–1.185)	(–1.205)	(–1.018)	(–1.019)	(–0.989)
Origin France	–0.088*	–0.071+	–0.072+	–0.060	–0.059	–0.059
	(–2.233)	(–1.800)	(–1.840)	(–1.525)	(–1.504)	(–1.499)
Origin Italy	0.019	0.016	0.009	0.014	0.015	0.018
	(0.451)	(0.369)	(0.209)	(0.332)	(0.358)	(0.429)
Has been producer (ln)	–0.417***	–0.397***	–0.405***	–0.393***	–0.395***	–0.395***
	(–13.694)	(–13.125)	(–13.381)	(–12.977)	(–13.018)	(–12.973)
Has been director (ln)	–0.035*	–0.023	–0.019	–0.014	–0.011	–0.004
	(–2.238)	(–1.391)	(–1.230)	(–0.860)	(–0.673)	(–0.235)
Titles in English (ln)	–0.287***	–0.275***	–0.272***	–0.266***	–0.264***	–0.261***
	(–16.648)	(–15.789)	(–15.759)	(–15.231)	(–15.124)	(–14.911)
US productions (ln)	0.668***	0.669***	0.647***	0.653***	0.653***	0.652***
	(41.120)	(40.562)	(39.739)	(39.696)	(39.705)	(39.584)
Major titles (ln)	–0.144***	–0.207***	–0.205***	–0.225***	–0.225***	–0.224***
	(–8.108)	(–11.665)	(–11.562)	(–12.690)	(–12.712)	(–12.655)
Sequels (ln)	–0.170***	–0.178***	–0.182***	–0.186***	–0.184***	–0.181***
	(–12.984)	(–13.704)	(–13.910)	(–14.233)	(–14.095)	(–13.867)
Novels (ln)	0.119***	0.134***	0.113***	0.124***	0.124***	0.126***
	(10.917)	(12.342)	(10.361)	(11.342)	(11.312)	(11.500)
Crew size (ln)	–0.009	–0.089***	0.038***	–0.030***	–0.031***	–0.032***
	(–1.152)	(–11.166)	(4.978)	(–3.521)	(–3.709)	(–3.823)
Genre: Thriller/Crime	–0.040***	–0.034***	–0.025***	–0.018***	–0.017**	–0.017**
	(–8.271)	(–6.920)	(–4.738)	(–3.337)	(–3.148)	(–3.146)
Genre: Family/ Adventure/Comedy	0.026***	0.020***	0.049***	0.050***	0.051***	0.051***
	(5.696)	(4.435)	(8.862)	(8.991)	(9.131)	(9.179)
Genre: Action/ Adventure/Western	0.010*	0.010*	0.012**	0.013**	0.013**	0.012**
	(2.357)	(2.237)	(2.658)	(2.948)	(3.006)	(2.634)
Genre: Drama/ Romance/History	0.069***	0.072***	0.109***	0.111***	0.112***	0.113***
	(13.063)	(13.465)	(17.852)	(17.846)	(18.030)	(18.120)
Person per movie ratio	0.018***	0.026***	0.029***	0.030***	0.030***	0.030***
	(12.841)	(18.055)	(19.533)	(20.373)	(20.354)	(20.368)

Table 2, continued

Team familiarity (ln)		–0.299*** (–5.442)		–0.208*** (–3.848)	–0.123* (–2.103)	–0.215*** (–3.948)
Recurring cohesion (ln)		0.321*** (25.485)		0.235*** (16.666)	0.194*** (12.667)	0.237*** (16.800)
Share of newcomers (ln)			–1.521*** (–30.333)	–0.928*** (–15.240)	–0.921*** (–15.119)	–0.620*** (–9.069)
Niche width (ln)			–0.309*** (–14.736)	–0.289*** (–13.619)	–0.292*** (–13.762)	–0.243*** (–10.342)
Genre diversity (ln)			–4.142*** (–29.084)	–3.241*** (–20.866)	–3.222*** (–20.739)	–2.974*** (–16.819)
Female*familiarity					–0.272* (–2.366)	
Female*cohesion					0.128*** (5.525)	
Female*newcomers						–0.887*** (–9.663)
Female*niche width						–0.143*** (–4.453)
Female*genre diversity						–0.614* (–2.281)
Log-likelihood	–405463.302	–405029.368	–404965.115	–404797.145	–404778.895	–404725.585
Chi^2	6233.637	7229.102	7398.253	7757.575	7767.220	7798.505
AIC	810974.604	810110.735	809984.230	809652.289	809619.791	809515.170
N (actors)	101090	101090	101090	101090	101090	101090
N (actor-film observations)	1237700	1237700	1237700	1237700	1237700	1237700

Note: $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$; *t* statistics in parentheses; two-sided tests; ln=logged variable.

same direction. Actors born in English-speaking countries face greater career hazards, whereas French or German actors have greater chances for career survival.[4] Crew size is negative in most models. This means that being part of a production with a larger crew and probably with a larger budget reduces the risks for failure and increases career duration time.

Models 2–4 add the main predictors to the model. Model 2 enters the first set of predictors: familiarity and cohesion. Model 3 includes the second set (share of newcomers, niche width, and genre diversity). In Model 4, all main predictors are included together. As can be seen from the results, interpersonal familiarity reduces the likelihood of failure, whereas recurring cohesion considerably increases it. In previous model estimations, which are not shown but can be made available upon request, the familiarity

4 This is partly due to a success bias for non-US actors in the sample, in which I included all actors who appeared in a US production at least once in their career. It is clear that actors from other countries selected for the sample are to some extent, at least in terms of international visibility, the most successful ones from their home countries. However, since I control for country of origin as well as for human capital and career success measures, this possible selection bias is largely negligible and does not affect the main research question.

effect is positive at first and then turns negative after the cohesion variable is included in the model. This speaks to what Uzzi and Spiro (2005) argue in their paper on collaboration and performance in musical productions, namely that social capital has a nonlinear, u-shaped effect. Here I demonstrate this for individual careers: on one side, a certain degree of trust and social capital in terms of "familiar" structures, measured by dyadic repeated collaborations, works to benefit the advancement of careers. On the other, too much social capital, measured here in terms of durable, recurring cohesion of 3+ cliques, becomes a form of overembeddedness that works against career advancement.

The coefficients of the information/genre diversity variables all point in the same direction and show negative signs. This means that chances for career survival are increased if actors pursue their career in open teams with greater genre diversity and higher percentages of newcomers. In addition, as the niche width variable shows, they have greater survival rates when they occupy a broader genre portfolio.

How do these effects vary between female and male actors? Can women reduce their disadvantaged position through open network structures, as suggested by the hypotheses? Models 5 and 6 specify interaction effects between the female dummy and the network and information/genre diversity predictors. The signs of the interaction terms support both hypotheses *H1* and *H2*. In order to facilitate interpretation, I follow Brambor, Clark, and Golder (2006: 73) and display the entire range of values of the interaction effects in a marginal effects diagram. The standard coefficient of the multiplicative interaction term in the regression model does not reveal enough substantial insight, since its value depends on the values of the constitutive terms and only refers to a single scenario – that is, when one of the constitutive variables is zero. Displaying the marginal effects graphically allows us to examine how and with what statistical precision the effects change over time across the whole range of meaningful values.

Figures 1 and 2 graph the interaction effects. The figures show point estimates of the model-based conditional marginal effects of the gender dummy across the whole range of values for the respective predictor, keeping constant all variables of the full model. The figures also graph the upper and lower bounds of the 95-percent confidence interval. The effects are significant at 95 percent when the y-zero line is outside the interval. As can be seen from Figure 1, *H1* is supported. The differences in the likelihood of career survival between male and female actors clearly become stronger as the cohesion variable increases. At the same time, gender disadvantages are reduced with higher degrees of familiarity, after I have controlled for cohesion and all other variables in the model. Figure 2 graphs the interaction effects of the diversity variables. Again, results support *H2*. The differences between males and females in career survival become less strong as information diversity and team openness increases. The broader the niche width, the more newcomers in a team, and the greater the team's genre diversity, the better the chances become for women, or, to put it differently, the more equal is the duration of a career between males and females.

Figure 1 Marginal effects of the female dummy on the risk of career failure, conditional on social capital measures, with 95-percent confidence levels

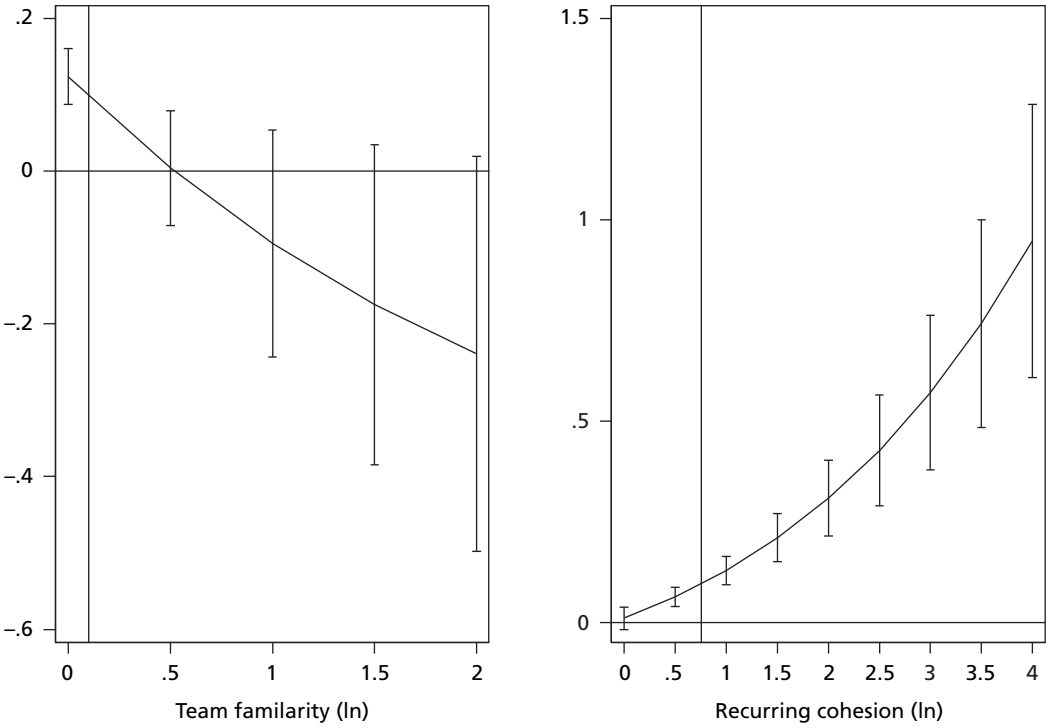

Figure 2 Marginal effects of the female dummy on the risk of career failure, conditional on diversity measures, with 95-percent confidence levels

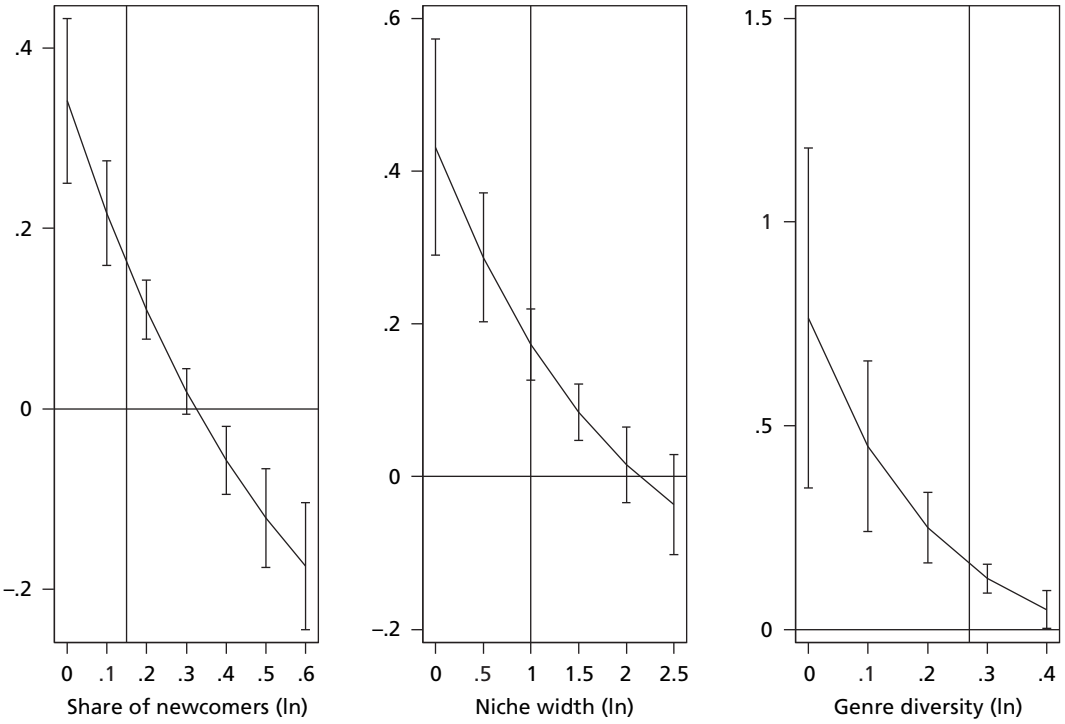

Table 3 Robustness checks

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	0.148***	0.148***	0.095***	0.507***	0.147***	1.200***
	(24.137)	(24.177)	(12.140)	(10.446)	(9.206)	(11.931)
Age (ln)	0.298***	0.299***	0.299***	0.300***	0.686***	0.687***
	(32.772)	(32.948)	(32.930)	(33.028)	(33.896)	(33.968)
Number of movies produced (ln)	–0.717***	–0.703***	–0.706***	–0.709***	–1.479***	–1.485***
	(–69.259)	(–65.837)	(–65.916)	(–66.082)	(–67.332)	(–67.497)
Cumulative number of awards (ln)	–0.532***	–0.533***	–0.532***	–0.531***	–1.157***	–1.160***
	(–27.787)	(–27.965)	(–27.940)	(–27.919)	(–25.300)	(–25.333)
Cumulative billing position (ln)	0.027***	0.027***	0.027***	0.028***	0.061***	0.061***
	(10.197)	(9.997)	(10.258)	(10.363)	(11.171)	(11.187)
Number of roles not credited (ln)	0.068***	0.066***	0.069***	0.070***	0.164***	0.165***
	(13.248)	(12.907)	(13.451)	(13.623)	(14.373)	(14.441)
Origin USA	0.031***	0.031***	0.029***	0.028***	0.031*	0.029+
	(4.286)	(4.252)	(4.077)	(3.946)	(2.054)	(1.935)
Origin UK	0.091***	0.091***	0.089***	0.089***	0.163***	0.162***
	(6.872)	(6.876)	(6.694)	(6.667)	(5.882)	(5.834)
Origin Germany	–0.014	–0.013	–0.012	–0.012	–0.065	–0.065
	(–0.693)	(–0.612)	(–0.603)	(–0.598)	(–1.462)	(–1.458)
Origin France	–0.041*	–0.042*	–0.041*	–0.042*	–0.070	–0.071
	(–2.108)	(–2.140)	(–2.104)	(–2.118)	(–1.613)	(–1.631)
Origin Italy	0.037+	0.036+	0.037+	0.039+	0.052	0.057
	(1.755)	(1.733)	(1.775)	(1.872)	(1.152)	(1.250)
Has been producer (ln)	–0.193***	–0.192***	–0.196***	–0.196***	–0.416***	–0.414***
	(–11.141)	(–11.153)	(–11.326)	(–11.315)	(–10.441)	(–10.370)
Has been director (ln)	0.024*	0.022*	0.025*	0.028**	0.054*	0.060*
	(2.326)	(2.115)	(2.391)	(2.665)	(2.245)	(2.502)
Titles in English (ln)	–0.114***	–0.114***	–0.113***	–0.112***	–0.297***	–0.295***
	(–13.608)	(–13.662)	(–13.509)	(–13.333)	(–14.784)	(–14.628)
US productions (ln)	0.328***	0.328***	0.329***	0.329***	0.773***	0.772***
	(41.201)	(41.201)	(41.297)	(41.162)	(40.520)	(40.442)
Major titles (ln)	0.078***	0.071***	0.072***	0.073***	0.077***	0.079***
	(7.973)	(7.283)	(7.325)	(7.405)	(3.827)	(3.939)
Sequels (ln)	–0.072***	–0.075***	–0.074***	–0.074***	–0.137***	–0.137***
	(–11.244)	(–11.534)	(–11.348)	(–11.348)	(–9.428)	(–9.423)
Novels (ln)	0.103***	0.100***	0.100***	0.102***	0.267***	0.269***
	(18.903)	(18.300)	(18.335)	(18.546)	(22.167)	(22.352)
Crew size (ln)	–0.021***	–0.020***	–0.021***	–0.021***	–0.041***	–0.041***
	(–4.740)	(–4.598)	(–4.846)	(–4.848)	(–4.592)	(–4.590)
Genre: Thriller/Crime	–0.031***	–0.031***	–0.030***	–0.030***	–0.063***	–0.063***
	(–11.466)	(–11.464)	(–11.161)	(–11.220)	(–11.130)	(–11.193)
Genre: Family/ Adventure/Comedy	0.017***	0.017***	0.018***	0.018***	0.039***	0.039***
	(5.732)	(5.821)	(6.157)	(6.138)	(6.500)	(6.473)
Genre: Action/ Adventure/Western	0.022***	0.023***	0.023***	0.022***	0.041***	0.039***
	(9.981)	(10.100)	(10.347)	(9.798)	(9.112)	(8.545)
Genre: Drama/ Romance/History	0.015***	0.015***	0.016***	0.016***	0.038***	0.038***
	(4.567)	(4.589)	(4.874)	(4.834)	(5.619)	(5.618)
Person per movie ratio	0.031***	0.031***	0.031***	0.032***	0.076***	0.076***
	(40.516)	(40.617)	(40.651)	(40.924)	(44.810)	(45.025)

Table 3, continued

Team familiarity (ln)	0.038 (1.539)	0.035 (1.438)	0.066* (2.504)	0.031 (1.235)	0.092 (1.609)	0.015 (0.281)
Recurring cohesion (ln)	0.053*** (7.987)	0.053*** (7.947)	0.021** (2.799)	0.056*** (8.388)	0.066*** (4.037)	0.154*** (10.561)
Share of newcomers (ln)	–0.141*** (–4.636)	–0.144*** (–4.739)	–0.140*** (–4.591)	0.079* (2.310)	–0.248*** (–3.853)	0.265*** (3.579)
Niche width (ln)	–0.101*** (–9.445)	–0.101*** (–9.447)	–0.104*** (–9.785)	–0.077*** (–6.550)	–0.200*** (–8.995)	–0.130*** (–5.245)
Genre diversity (ln)	–0.990*** (–12.278)	–0.975*** (–12.081)	–0.967*** (–11.969)	–0.776*** (–8.341)	–1.992*** (–12.067)	–1.441*** (–7.502)
t^1	0.028*** (32.351)	0.023*** (14.754)	0.023*** (14.778)	0.023*** (14.846)	0.042*** (14.707)	0.042*** (14.753)
t^2	–0.000 (–0.822)	0.000*** (3.772)	0.000*** (3.752)	0.000*** (3.667)	0.001*** (5.105)	0.001*** (5.052)
t^3		–0.000*** (–3.830)	–0.000*** (–3.822)	–0.000*** (–3.757)	–0.000*** (–6.501)	–0.000*** (–6.474)
Female*familiarity			–0.103+ (–1.834)		–0.241* (–2.074)	
Female*cohesion			0.107*** (9.431)		0.261*** (10.785)	
Female*newcomers				–0.673*** (–14.662)		–1.510*** (–15.599)
Female*niche width				–0.080*** (–4.920)		–0.200*** (–5.958)
Female*genre diversity				–0.516*** (–3.767)		–1.466*** (–5.294)
Constant	–2.604*** (–58.755)	–2.602*** (–58.950)	–2.586*** (–58.565)	–2.736*** (–57.117)	–5.358*** (–55.863)	–5.745*** (–55.248)
Pseudo R^2	0.146	0.146	0.146	0.147		
Log-likelihood	–148517.701	–148502.085	–148428.796	–148339.974	–148314.439	–148229.087
Chi^2	29838.753	29996.661	30000.705	30065.986	35518.105	35725.779
AIC	297099.403	297070.170	296927.591	296751.948	296698.877	296530.173
N (actors)	101090	101090	101090	101090	101090	101090
N (actor-film observations)	1237700	1237700	1237700	1237700	1237700	1237700

Note: $^+p<0.1$, $^*p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$; *t* statistics in parentheses; two-sided tests.

In addition, Table 3 tests the robustness of the results. These tests show that the results are not sensitive under different specifications and that the main effects remain unaffected. In particular, I use discrete-time estimations using probit regressions with different specifications of time (quadratic and cubic polynomials in Model 1 and 2), as suggested by Carter and Signorino (2010). Model 3 and 4 add the interaction effects to the cubic specification. As can be seen, results remain robust and do not change. Model 5 and 6 specify a complementary log-log regression, as recommended by Buckley and Westerland (2004), or as used by Dobbin et al. (2011). Again, the interaction effects do not differ. To sum up, results are not driven by a specific estimation method. Hence, the two hypotheses are supported by this analysis. The results can be regarded as robust.

5 Discussion and conclusion

On the basis of a large-scale, longitudinal career database consisting of more than a hundred thousand film actors and covering over one million film engagements, this study analyzed how measures of cohesion, social capital, and information diversity moderate gender disadvantages in pursuing careers in film. On the basis of previous case-study research and reasoning from social network theory, I argued that women are likely to suffer from cohesive social structures but can take advantage of less cohesive, weaker structures that are more open with regard to job-relevant information flow. In order to test these assumptions, I employed interaction effects between gender and different measures of social capital and information diversity on career survival hazards. The presented results support the proposed assumptions: gender disadvantages grow significantly with increases in team cohesion, but differences are reduced in teams with weaker social ties and higher degrees of information diversity. If women pursue their career in open and diverse network architectures, they can reduce their disadvantaged position and the risk of dropping out of the business to a level that is statistically indistinguishable from the risk men run. The more open and diverse team structures become, the more gender equality can be expected in project-based career advancement.

The findings of this study contribute valuable insights in at least four different ways. First, the study shows how and what type of social capital works in favor of or against disadvantaged labor market groups. It should be noted that this study focuses on careers in which gender disadvantages do not result from direct competition between males and females – male and female jobs are mostly predefined with the film's script – but rather from disadvantages at an aggregate level. The sociological causes of these disadvantages lie beyond the scope of this study. Gender disadvantages might be induced through processes of allocative discrimination (Petersen/Saporta 2004), through motherhood penalties, or through discrimination by gatekeepers based on ascriptive rather than meritocratic judgments. Differences in careers between males and females might also be induced through self-inflicted changes in personal preference structures, yielding different human capital investments across genders (e.g. Becker 1975). What this study contributes instead is to show how observed career inequalities between males and females decrease or increase through different forms of network embeddedness. In doing this, the article particularly shows that careers in cohesive networks can be a "double jeopardy" (Lincoln/Allen 2004) for women who already face disadvantaged labor market conditions.

Second, in the literature it has been rarely studied how different mechanisms of inequality interact with each other. Do they lessen or intensify the severity of inequality, and if so, how? As consequence, cumulative or conditional effects of inequality have remained poorly understood. By analyzing interaction effects on individual career data, this study is able to capture the conditional nature of social inequality. Hence, it contributes to a better understanding of the complex effects, multiple or cumulative, between different

factors of social inequality (DiPrete/Eirich 2006). Moreover, this study shows that inequalities inherently depend on factors that are social by nature and therefore heeds the call to study more seriously the *social structures* of inequality (Lutter 2012b).

Third, it was the purpose of this study to systematically analyze assumptions which have been long discussed in the literature but never quantitatively stated. Single-case studies have showed us that women are disadvantaged in labor markets based on informal recruitment practices through interpersonal networks. To the best of our knowledge, this study is the first to examine these insights based on a large-scale longitudinal dataset, using sophisticated measures of social capital and information diversity. In doing this, it explores a unique dataset covering a labor market in its entirety, including all products that have ever been produced in that market and all actors who have been ever involved in making these products. Seldom in sociological research have we been able to gain insights from a full population of labor market actors.

Fourth, although the empirical setting is based on a specific artistic labor market, I believe that the findings can be generalized beyond this cultural industry and expanded to other flexible, project-based labor markets. Examples could be the market for managers, architects, journalists, designers, academics, or even engineers working in fast-changing high-tech areas. Future research could and should try to apply the indicators used here to these other fields. It would be especially interesting to look at careers in which jobs are not pre-defined for males and females, but are open and competitive to both genders. It would be interesting to see if the same results can be obtained. This would not only prove and validate the findings presented here but would contribute to an advanced understanding of how inequalities emerge, why they intensify, and, most important, under what conditions inequalities disappear.

6 Appendix

Table A1 Awards used for this study

Awards USA	International "A" festivals	International "B" festivals
Academy Awards	Berlin International Film Festival	European Film Awards
Broadcast Film Critics Association Awards	Cairo International Film Festival	German Film Awards
Directors Guild of America Awards	Cannes Film Festival	Ghent International Film Festival
Golden Globe Awards	International Film Festival of India	London Critics Circle Film Awards
Independent Spirit Awards	Karlovy Vary International Film Festival	London Film Festival
Laurel Awards	Locarno International Film Festival	Miami International Film Festival
Los Angeles Film Critics Association Awards	Mar del Plata Film Festival	Monaco International Film Festival
MTV Movie Awards	Montreal World Film Festival	Moondance International Film Festival
National Board of Review Awards	Moscow International Film Festival	Norwegian International Film Festival
National Society of Film Critics Awards	San Sebastian International Film Festival	Sarajevo Film Festival
New York Film Critics Circle Awards	Shanghai International Film Festival	Seattle International Film Festival
People's Choice Awards	Tokyo International Film Festival	Thessaloniki Film Festival
Screen Actors Guild Awards	Venice Film Festival	Toronto International Film Festival
Writers Guild of America Awards	Warsaw International Film Festival	Undine Awards, Austria
		Vienna International Film Festival
		Zurich Film Festival

Table A2 Rotated factor loadings and unique variances, from principal component factor analysis

Genre	Factor 1 Thriller/ Crime	Factor 2 Family/ Adventure/ Comedy	Factor 3 Action/ Adventure/ Western	Factor 4 Drama/ Romance/ History	Uniqueness
Short	–0.2052	–0.1457	–0.2466	–0.3365	0.7626
Drama	0.1079	–0.1662		0.7106	0.4466
Comedy	–0.1953	0.243	–0.5792	–0.1944	0.5295
Romance	–0.1121	0.2432	–0.1073	0.3886	0.7658
Action	0.2198	0.2652	0.5413		0.5851
Animation		0.5289		–0.108	0.7039
Thriller	0.6741		0.1727		0.5137
Family		0.6406			0.5704
Crime	0.5547			0.2781	0.6134
Adventure		0.5193	0.4661		0.5102
Music	–0.1889		0.1553		0.9357
Horror	0.3881			–0.3283	0.7309
Fantasy		0.5506			0.6872
Mystery	0.5278				0.7197
Sci-fi	0.2638	0.2219	0.2365	–0.3157	0.7256
Western	–0.1933		0.3326	–0.2806	0.764
Musical	–0.1371	0.1933	–0.2804		0.8559
Biography	–0.244		0.2574	0.2675	0.7945
Sport				0.1385	0.9651
War	–0.1923		0.3311	0.3173	0.7526
History	–0.2594		0.4021	0.2751	0.6928
Film noir	0.2969			0.2216	0.8486
Adult					0.9873
Reality					0.9997
News					0.993
Game show					0.9991
Documentary	–0.23	–0.2509	0.1886	–0.237	0.7924
Talk show					0.9993

Note: Blanks represent factor loadings <.1.

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