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Tripping yourself up? Team Formation and Effective Teams

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Abstract

Recruiting key members in project-teams is a complex decision-making process difficult to unpack. For project-teams finding the right match is critical. Project stakeholders choose individuals they believe are the best fit for their project. To choose a new member, incumbents have to rely on heuristics, which might lead them to pick individuals that will not be the best placed to help the project succeed. We uncover the criteria and behavioral patterns incumbents use while hiring new team members. We explore more specifically the effects of similarity and fit. Our contribution highlights discrepancies between the heuristics used to make hiring decisions and characteristics of team members that lead to better performance for the project. More specifically, we show that similarity has a u-shaped relationship with the likelihood of a newcomer being hired but no relationship with future performance of the team formed. Project specific expertise has a negative impact on the likelihood of being hired despite having a strong positive impact on the future performance of the team.

We test our theory in the French film industry, exploring the implications beyond this industry for high-stake matching decisions of skilled labor to projects, and for managers involved in recruiting decisions.

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ABSTRACT

Recruiting key members in project-teams is a complex decision-making process difficult to unpack. For project-teams finding the right match is critical. Project stakeholders choose individuals they believe are the best fit for their project. Constraints during the recruitment process, in terms of time and resources, imply that decisions are made under uncertainty on the quality of the new addition to the team. As a result, project stakeholders rely on certain signals of quality more than others to reduce uncertainty. We uncover which of those signals and behavioral patterns incumbents use while hiring new team members. We explore more specifically the effects of similarity and fit. Our contribution highlights discrepancies between the signals stakeholders rely upon to make hiring decisions and characteristics of team members that lead to better performance for the project. More specifically, we show that similarity has a u-shaped relationship with the likelihood of a newcomer being hired but no relationship with future performance of the team formed. Project specific expertise has a negative impact on the likelihood of being hired despite having a strong positive impact on the future performance of the team. We test our theory in the French film industry, exploring the implications beyond this industry for high-stake matching decisions of skilled labor to projects, and for managers involved in recruiting decisions.

Keywords: dynamic network, homophily, team, 2-mode network, project-based industry.

Team formation has been a longstanding interest in organizational research and a crucial problem for entrepreneurs and innovative projects stakeholders. In entrepreneurial or innovative settings, failing to pick the right team member can turn success into failure. For this reason, rather than only focusing on team performance, we also focus on one antecedent of it: team formation. We believe that by understanding mechanisms of team formation (what leads incumbents to choose a newcomer) we will further our understanding of differentials in performance between teams. It is not enough to study the influence of team composition on performance if we do not know what processes lead teams to have a certain set of members. Indeed, it overlooks the potential hurdles in the formation process that can prevent teams from having a composition ideal for performance. This simple question has received surprisingly little attention, but prior literature has closely investigated related questions.

The first of those questions is the influence of team composition on team performance. Prior literature has studied the performance implications of team composition. This literature shows that diversity in backgrounds (both in terms of number of different employers' team members worked for and functional diversity) of team members makes an entrepreneurial team more likely to reach an IPO (Beckman et al. (2007). In the film industry, a combination of experienced professionals and newcomers has a positive effect on team innovation (Perretti & Negro (2007). Studies have also investigated the extent to which team performance depends on how well a star blends into a team, team familiarity facilitate blending, which in turn benefits performance (Cattani et al. (2013). Other studies point to the importance of homophily (Reagans et al. (2004) and familiarity (Ferriani et al. (2009) among team members as an antecedent of team performance. However, such studies are concerned with established teams and do not investigate the process of team formation.

A few related studies investigate team formation processes more directly. Team composition has been studied as the result of two processes: a team-level and an organizational level process (Perretti & Negro (2006). They show that team design in an organization is constrained by team members' status and organizational structure. Reagans et al. (2004) have studied two competing heuristics that managers can use to make the team: demography (i.e. education, tenure) and network characteristics. They show that relying on social network characteristics to assemble teams is often a better alternative, especially because there are constraints on how a manager can manipulate demography within a team. Finally, Ruef et al. (2003) found support for certain types of homophily (gender, ethnicity and occupation) as driving team composition in entrepreneurial settings. However, each of those studies focuses on global team composition. We argue that team composition is an emergent process and in order to study it, one needs to study processes that lead to individual member's enrollment.

Those studies answer important questions but leave crucial parts of the mobilization process in the shadows, especially in relation to the making of the team. The biggest blind spot is probably the antecedents of team composition: the existing literature does not assess processes leading to better team composition for performance, only whether or not it was obtained. We intend to open the black box of such processes. At the individual level, whilst incumbents use certain norms and values to pick new members, they also suffer from cognitive biases that have been well studied: individuals perceived as similar are seen as more attractive exchange partners (McPherson et al. (2001); Vissa (2011). Effectively, social networks are prisms that inform how others are perceived (Podolny (2001). Mechanisms at play during the selection process lead to team members recruiting others they feel are a better fit for the project and will help the team succeed. However, there might be a discrepancy between this perception and reality. We see our contribution in unpacking team formation through studying recruitment decisions instead of looking at team composition ex-post.

Studying similarity between incumbents and potential newcomers, we contribute to a better understanding of the determinants of team composition. The second part of our contribution is to evaluate the impact of team formation on team performance.

We further prior literature by acknowledging that hiring decisions are consensus decisions on the part of the incumbents, offering a framework to understand how consensus is structured, and studying the relative position of newcomers to each incumbent. We study the influence of homophily and expertise on hiring decisions. We then show the influence of these two dimensions on performance in realized teams.

We consider both individual and dyadic characteristics in a dynamic way. In order to study new team member recruitment, we need a setting in which additions to the team are a common events. The French film industry is a relevant context for our study for several reasons. First, project stakeholders, directors and producers, conjointly decide who they are going to hire as their main technical contributors. The choice of technicians is a cleaner setting than choice of actors, as it is less prone to fads and budget constraints as well as project bundles in which talent-agents offer packaged deals comprising an actor, a director and the scenario to production companies (Bielby & Bielby (1999). This makes us confident that choices are the result of a consensus between directors and producers on the perceived fit of the technician for the project. Exploring the differences between what influences the likelihood of a technician being hired and what influences team success, we further our knowledge of team formation mechanisms and of their potential to hinder the formation of effective teams.

The following sections offers a review of the research our framework builds upon and develops our hypotheses, before describing the data and methods in detail, and presenting the

results of our analysis. The final section discusses our results and their implications for management theory and practice.

TEAM FORMATION MECHANISMS: THEORY AND HYPOTHESIS

Prior studies have examined how team composition affects performance, but have overlooked how individual team members' characteristics shape recruitment decisions. Team composition is an emergent process resulting from successive selection and recruitment decisions by incumbents. Thus, to further our understanding of team composition and its influence on performance, it is necessary to study antecedents of team composition at the enrollment decision level. As Figure 1 shows, team formation should be understood as a process from which team composition is attained. We study recruiting decisions because we believe it is the relevant unit of analysis to understand team formation processes. The agregation of those decisions leads to team composition and, from there, constrain or enable team performance.

Insert Figure 1 about here

Building on the team composition literature, we focus on expertise similarity between the incumbents and the potential newcomers and on expertise fit between the potential newcomers and the requirements of the project at hand.

The social network literature abounds with evidence that similarity increases the likelihood of a connection between two individuals, this is known as the 'homophily principle' (McPherson et al. (2001). In the management literature, a significant body of evidence shows the importance of homophily to secure resources. For example, homophilous ties bring greater returns in the workplace (Ibarra (1992). In contexts where homophily should be low, such as a mixer, researchers found that the duration of interactions with a new group of

people increased if some homophily existed between the individual and one of the group members (Ingram & Morris (2007). This leads us to think homophily is a highly relevant dimension to consider when studying team formation because it is likely to influence the way incumbents make decisions on which newcomer to hire.

Expertise Similarity

From the perspective of homophily as a prism (Podolny (2001), one assumes that similarity changes the way two individuals see each other. In that perspective, studies on tie formation have found that within the constraint of the organization, individuals choose to form ties with individuals who are similar (Kleinbaum et al. (2013). In scientific collaboration, homophily in terms of status with a potential partner has a positive effect on tie formation (Dahlander & McFarland (2013). This leads us to believe that incumbents are more likely to choose newcomers that have similar expertise to themselves.

Expertise similarity reflects underlying shared knowledge and cultural references. This overlap means that the cultural proximity of the individual will facilitate communication between them.

Prior research has increasingly recognized the importance of shared language and culture within organizations both to predict the formation of ties and to understand how effective they are for innovative purposes (Kogut & Zander, 1992; Vissa, 2011). Recent studies of scientific collaborations have shown that knowledge and culture overlap have an inverted-U relationship with the likelihood of forming ties. This means that overlap increases the likelihood of a tie being formed up to a certain point, but past this limit, an increase of overlap decreases the likelihood of a tie being formed (Dahlander & McFarland (2013). This leads us to believe that a potential team member has a greater chance of being hired if he or

she shares expertise with the incumbents, and this will lead to teams that exhibit greater expertise homophily among their members.

If a director or a producer have similar expertise in certain types of films to that of a cinematographer, they are more likely to have common references when approaching a new project. This makes them more prone to agree on what is the essence of the current project. They are, for example, more likely to have the same movies in mind when trying to describe the shape the new ventures will take. This in turn will facilitate consensus around stylistic choices.

However, it is not clear that homophilous teams perform better than heterogenous ones. For example, start-up teams whose members have diverse prior company associations are more likely to achieve an IPO than homophilous teams (Beckman et al., 2007). Research on the film industry has showed that teams bringing together newcomers and old timers, in other words that display diversity in terms of experience, are more innovative (Perretti & Negro, 2007). Knowledge variety within a team, understood as experience in different industries, is beneficial to team creativity (Han et al., 2013). Finally, differences in experience (between newcomers and old-timers) positively impact team creativity (Ferriani et al., 2009).

In line with those past efforts, we argue that the anticipation of easier coordination due to shared cultural references will make the director and producer more likely to hire a cinematographer that has expertise similar to theirs. However, too much overlap will be perceived by the project stakeholders as the new hire not adding any expertise diversity to the team and might reduce their likelihood of hiring them.

The implications of expertise overlap for team performance are similar to those for hiring. We expect that shared expertise will have an inverted U-shaped relationship with team

performance. Teams with complete separation of past expertise between incumbents and newcomers will have trouble collaborating and thus experience relatively lower performance. As overlap in expertise increases, teams will perform better because collaboration will become easier from sharing cultural references, while retaining sufficient diversity of experience. Once the overlap increases to higher levels, the negative effect of the lack of diversity in expertise will overcome the benefits of easier collaboration and average team performance will drop. Thus:

Hypothe*sis 1: Overlap in terms of genre expertise between the cinematographer's past movies and the team members' past movies will have an inverted U*-shaped relationship with the likelihood of a cinematographer being hired.

Hypothesis 2: Overlap in terms of genre expertise between the cinematographer and the other team members will have a negative curvilinear relationship with the performance of the movie.

Project specific expertise

Homophily in terms of genre can also be evaluated at the project level. This is akin to the typecasting phenomenon, where someone is hired repeatedly for similar projects based on the assumption that they will perform better on those projects (Zuckerman et al., 2003). In this situation, the mechanism at play is the perceived fit between the cinematographer's expertise and the project at hand. Producers and directors will want to reduce the risk associated with the project by hiring someone who can bring relevant expertise to the project. New members are seen as a source of human capital relevant for the project at hand (Faulkner & Anderson, 1987). Therefore, we argue that project stakeholders will hire cinematographers who have extensive expertise in the genre of their project. It is straightforward to assume that people

with prior expertise on similar projects will individually perform better on average and will contribute to better overall performance of the projects in which they are engaged. Thus we hypothesise:

Hypothesis 3: Fit in terms of genre between the films the cinematographer has worked on and the focal film will increase the likelihood of the cinematographer being hired.

Hypothesis 4: Fit of the cinematograph*er's experience with the project at end increases the* likelihood of the project being successful.

DATA AND METHODS

The film industry is ideal for our study because team formation is repeated for each movie project (Faulkner & Anderson, 1987; Bielby & Bielby, 1999). As a result, heuristics used by team members when making recruiting decisions are easier to identify. We focus on the French film industry for several reasons. First, specific labor legislation makes remuneration rates between technicians comparable and drives out the risk that choices are governed mainly by monetary incentives, which we cannot observe. Second, producers and directors work jointly to recruit cinematographers and their decisions are reached by consensus. Finally, we have very detailed information about collaboration and projects from different sources, which allows us to closely observe team formation occurrences during the period of the study.

Data sources

The data on the French movie industry is obtained through the Lumiere database which is a European Union project (http://lumiere.obs.coe.int/). The data covers films released in France between 1996 and 2010 (over 99% coverage). It provides us with the title of the movie, its

ISAN number (unique identifier for intellectual property purposes), a link to its Internet Movie DataBase (IMDB) page, the name of the director, the producing country or countries, the production year, whether or not it has received funds from the European cinema programmes and the number of entries in each of the European markets the movie has been released in. The relational data on those movies is drawn from IMDB. The resulting data is completed and validated with other sources (professional publications and listings) where necessary. In addition to the data previously mentioned, we collect data on the genre of the movies from IMDB.

Our sample includes all movies identified in the database as French productions or co-productions, the core team members involved in recruiting (directors and producers) and the recruited cinematographer. The Lumiere database gives information on 3610 films over the period. Exclusion of re-release leads to a sample of 3555 films produced between 1996 and 2010. We removed an additional 204 movies due to missing data on producers (less than 6% of the sample). Of the remaining sample, we have complete information on career history of the producers, directors and cinematographers from 1996 to 2010. We use all the data in the sample to build our variables, but to minimize bias associated with left censoring of our data (we have no records prior to 1996), we exclude the first 4 years' worth of data from our analyses. We use the resulting sample in all the models developed to test our hypotheses.

The framework

Our objective is to evaluate the likelihood of a cinematographer being preferred to another by project stakeholders. In order to do this we need to compare a cinematographer hired on a project with others who could have been hired but were not. We do not have access to the list of cinematographers who were interviewed for each specific project. However, we can construct a pool of cinematographers who were available at the time that hiring took place.

We think this is sensible for two reasons. First, there are many more cinematographers available than jobs. Second, cinematographers are more substitutable than actors or directors, therefore, the project stakeholders are in a favorable position so there will be little competition for cinematographers, but a lot of competition between cinematographers for projects. As a result, our assumption that the decision is directed from the project stakeholders to the cinematographer is a close representation of reality. As a result, for each realized pair between a movie project and a cinematographer, we draw 4 control cases that pair the same project with different cinematographers available to work at the time.

The nature of our data allows us to test the effects of several types of dyadic similarity criteria to project-team members. The potential hire might be similar on one dimension to all incumbents (directors and producers), but the potential hire might be similar to the director and dissimilar to the producer on one dimension. This last case would be unaccountable for if we were to study aggregated similarity to the team. Indeed, if we were to measure this, both a situation like the one we outlined and a situation into which the newcomer is mildly similar to all incumbents would translate in the same medium level of aggregated similarity. However, it is not clear that the implications of those two configurations for recruitment and performance are identical. This is a significant departure from the traditional approach and allows a more fine-grained understanding of processes underlying team formation.

To do this, we need to overcome technical hurdles linked to running regression-like analyses on network data. We develop a framework that allows the study of dynamic 2-mode networks. It uses 2-mode network data without the need for projection (which is harmful to the data structure and can lead to overestimate connectivity and triadic closure, see Everett & Borgatti, 2012; Opsahl, 2011; Latapy et al., 2008). In addition, our approach evaluates processes at the individual and project level, along with their interplay, simultaneously. This

is an improvement over methods that rely on projection, as well as most multilevel attempts. However, this approach assumes that new hires do not occur simultaneously and their order is known. In our setting, this holds true in the majority of cases. Computationally, our framework is a modification of the one developed for 1-mode networks by Opsahl & Hogan (2010). The likelihood of the new match is estimated by growing the network tie by tie and examining each new tie in turn. After each new tie is added to the network, all the individuals' scores on each variable are updated. Each realized hire is compared to potential hires who were not chosen, drawn from the pool of technicians available to work. Below we explain in greater detail how we build the pool of technicians. We call it the risk set.

Building the risk set

Our approach compares characteristics of realized ties to potential ties. There are different strategies that one can adopt to build a risk set. Ultimately, this is a theoretical question which depends on the context of the study and the hypotheses one wants to test. In our case, the risk set must have one property to ensure the validity of our analysis: it needs to contain cinematographers that are available to work. We need to eliminate from the set inactive professionals and those already involved elsewhere at the time of the focal project. Determining which cinematographers are inactive is difficult. We rely on the assumption that the longer it has been since one has appeared in the credits of a movie the more likely it is that this person is no longer looking for employment in the industry. As a consequence we exclude from the risk set any professional that has not worked on a film for 4 years. It is also difficult to know precisely which professionals are already working, because we have access to exact shooting dates for only a limited number of projects. Here again, we rely on the assumption that professionals who have been involved with a movie produced the same year as the focal project are not available for the focal project. Therefore, we exclude from the risk

set individuals tied to a movie less than a year prior to the current movie. Our exclusion criteria are conservative and probably lead to the exclusion of a few available cinematographers from our risk set. However, for the robustness of our analysis, a conservative risk set is preferable to one that is overly inclusive.

Dependent variable

To test our hypotheses, we measure two different dependent variables. First, to assess which cinematographer is chosen for a specific project and, second, to measure performance of the resulting teams.

Realized collaboration — Our first dependent variable is the tie between a movie project and a cinematographer. These ties are ordered in a sequence based on the movie's release date. For the 213 movies for which we do not have the exact release date, we attribute a release date to them on the 1st of January of the year following their production. We think this is unproblematic because it only concerns a small portion of our sample and it is unlikely to change the order of many cinematographers' movie projects, given the small number of movies a cinematographer can do every year. Each realized tie is matched to unrealized ties to cinematographers in the risk set. The realized tie gets the value 1 on our dependent variables, the unrealized ones get 0. This allows us to estimate the influence of a professional' characteristics and of the dyad professional-project on the likelihood that this professional will be hired on a specific project.

Performance — We measure performance as the admissions generated by a movie. Admissions are measured as total admissions in France over the course of the exploitation of the movie. This amount is logged using a base 10.

Independent variables

Homophily — This is a similarity measure with specific incumbent members of the team (director and producer). When more than one person is credited with the director or producer position, the value for the director/producer experience is the average of the score of all individuals occupying this position on the movie. In those cases, homophily measures the distance between the cinematographer and the average of the multiple holders of a position. For example, if a movie has two producers who have participated in 2 and 5 movies respectively, the score for the producers experience will be the average of their experience, 3.5. This score will then be compared to the number of movies made by the cinematographer that is hired and the ones from the risk set to build homophily scores for each pair of stakeholders-cinematographer.

Expertise overlap — This variable measures the overlap in expertise between the cinematographer and the incumbent team members. Overlap in expertise is understood here as an overlap in genre expertise. To compute this measure, we look at the list of genres used to describe all the movies the cinematographer has been involved with and the list of genre used to describe the movies of an incumbent. This gives us two vectors that record for each genre, the number of movies the individual has done that were described using this genre. To obtain the proportion of their experience that was acquired in each genre, we divide these vectors by the total number of movies the individual has been involved with. We multiply the two vectors and sum the elements of the resulting vector to obtain a score of the expertise overlap for the dyad cinematographer-incumbent. For example, if a cinematographer has done 1 comedy and 2 dramas and a producer has done 1 drama and 1 musical, their expertise overlap is equal to $\frac{1}{3}(\frac{1}{3} \times 0 + \frac{2}{3} \times \frac{1}{2} + 0 \times \frac{1}{2})$. We compute two variables for expertise overlap: Expertise overlap with producer, Expertise overlap with director.

Project specific expertise — This variable measures the prior expertise of the cinematographer in movies of the same genre as the focal movie. This variable takes the value 1 if the cinematographer previously participated in a movie of the same genre as the current movie. It takes the value 0 otherwise.

Control variables

Faulkner & Anderson (1987) explored experience homophily as an important factor in the matching of directors to cinematographers. However, one has to be careful to disentangle the effects of homophily, past collaboration and generation effects. Indeed, a pattern of individuals collaborating with seemingly similar others in terms of experience can arise from the tendency of people who started on the market at the same time to collaborate together. These are more likely to share a direct tie or ties to the same third parties, making them more likely to collaborate. In addition, they are more likely to have similar levels of experience. This renders it crucial to conjointly measure experience and tenure homophily to disentangle their effects. Tenure homophily will reflect the tendency of individuals who started at the same time to collaborate together, while experience homophily will reflect the tendency of individuals who have participated in similar numbers of movies, and therefore have similar levels of experience in the workings of the industry, to collaborate together. Therefore, to assess the influence of Experience homophily, we need to control for Tenure homophily and Prior collaboration.

Tenure homophily — This homophily variable assesses the difference in terms of length of tenure in the industry between the cinematographer and the producer or the director. The variables are computed by taking the absolute value of the difference between the year the cinematographer participated in his/her first movie and the year the project stakeholder participated in his/her first movie in years. To make interpretation easier, the variable in our

models is the inverse of this value (with 1 added to the denominator to avoid dividing by 0). This means that the variable takes the value 1 if both individuals started their career at the same time and then becomes smaller and smaller the further apart their date of entry on the market is. For example, if a cinematographer participated in his/her first movie in 1996 and the director participated in his/her first movie in 2001, the value for tenure homophily between the cinematographer and the director will be 1/6 ($1 - \frac{1}{|1996-2001|+1}$). We compute two tenure homophily variables: one with the producer, tenure homophily with producer; and one with the director, tenure homophily with director.

Experience homophily — Faulkner & Anderson (1987) showed that directors and cinematographers tend to often work with individuals that have similar levels of experience (in terms of number of movies they have participated in). But the way the authors test for it does not fully allow to disentangle the effects of tenure on the market and of experience. We think it essential to be able to assess the effects of similarity of experience independent of the effects of tenure. The effect of similar levels of experience should lead incumbents to perceive individuals as a better fit for the project because this would minimize two effects. First, if the incumbent is the most experienced, she will find an individual with a lot less experience than her a bad fit for the project and a liability in terms of his ability to bring the project to fruition. Second, if the incumbent is the least experienced, she might be reluctant to hire a very seasoned professional because his/her experience will give her leverage to challenge the incumbent's influence on the project.

The variable assesses how close two people are in terms of experience, in number of movies. It is computed as $1 - \frac{|N_{cinematographer} - N_{producer}|}{maximum(N_{cinematographer}, N_{producer})+1}$, where N is the number of movies. For example, if the cinematographer has done 5 movies and the director has done 2,

the value of the experience homophily with director variable will be 0.5 ($1 - \frac{|5-2|}{5+1}$). This variable varies between 0 and 1. It is equal to 1 if the two individuals have participated in the same number of movies. It decreases linearly toward 0 as the difference in the number of participation in movies grows. We compute two experience homophily variables, one with the producer, experience homophily with producer and one with the director, experience homophily with director.

Prior collaborations — Scholars have looked at the importance or recurring collaboration (Ferriani et al. (2005); Zuckerman, 2004) in a seemingly free market, hinting to the fact that individuals develop a portfolio of collaborators early in their career and subsequently work mainly with members of this 'latent organization' (Ferriani et al., 2005). Prior research has argued that team familiarity reduces coordination costs and makes a team able to perform at its peak without an adaptation period (Groysberg & Lee, 2009; Cattani et al., 2012). From the incumbents' perspective, a past collaboration decreases perceived risks attached to the collaboration. For the producer, they can use the information about the previous collaboration to estimate costs and quality of the work. For the director, it is likely he will have developed communication routines with the cinematographer on the previous set. Therefore professionals a technician has already worked with are more likely to hire him/her again.

In the movie industry, evidence suggests that production is organized using a 'structured role system' where individuals are assumed to conform to behavior expected from those in their job title, which might reduce coordination costs in general, including when working with strangers (Bechky (2006). This reduces the incentive to re-hire technicians one has already worked with. In addition, working consistently with the same collaborators might prove detrimental to novelty and consequently to performance (Perretti & Negro, 2007; Sorenson &

Waguespack, 2006). As a consequence, there might be decreasing returns in working consistently with the same individuals.

The variable Prior collaborations records the number of past collaborations between a cinematographer and the project stakeholders. This is recorded independently for each team members. Prior collaboration with the director records the number of past collaborations with the director. Prior collaboration with the producer records the number of prior collaborations with the producer. In cases where a movie has more than one director or producer, we use the average number of past collaborations with the directors or producers. Controlling for past ties and tenure homophily helps ensure that the effects of experience homophily are not driven by those two dimensions of collaboration.

Experience — This counts the number of movies done by the cinematographer up to, but excluding, the date of the focal movie. This controls for the overall amount of experience of an individual. It is necessary to assure that the effect of experience homophily we are observing is not linked to the stock of experience but to the similarity in the stock of the cinematographer and the different project stakeholders.

Tenure — This records the year in which the cinematographer participated in his first movie. It controls for the overall length of a cinematographer's tenure.

Mean admissions — This variable records the mean number of admissions of all the movies the cinematographer has participated in up to the time of the current project. This average controls for a cinematographer's track record of being associated with financially successful projects, which is an heuristic used by producers and directors to select talents.

Estimation

To test our hypotheses, we estimate two series of models, one for each of our dependent variables, Realized collaboration and Performance. The first dependent variable records whether or not the individual has been hired on the specific movie project. The second one records performance of those hired. Time-variant individual and homophily measures are updated each time a new tie between a project and a cinematographer enters the collaboration network.

The models on hire are estimated using a conditional logit with errors clustered on ties (McFadden, 1973). Models are fitted in R, using the clogit routine in the package survival (R Core, 2013; Therneau, 2013). The models on performance of movies are linear mixed models with individual fixed effects. Models are fitted in R, using the lme4 package (Bates et al., 2013). We also ran robustness checks, running additional models excluding movies that had more than one cinematographer. The results were similar.

RESULTS

Table 1 presents the correlation between our variables. Overall, correlations are low. However, the correlation between the experience of a cinematographer and their tenure is relatively high (0.5, p=0.01). This is not very surprising as the longer a technician has been on the labor-market, the more likely he or she is to have participated in more projects. Homophily in terms of experience with the producer is also strongly negatively correlated with the experience of a cinematographer (-0.52, p=0.01). So the more experienced a cinematographer, the less likely he is to work with similarly experienced producers. This is explained by the high exit rate of the industry for producers (Cattani et al. (2008)): the base rate likelihood of working with a producer with similar experience decreases as a cinematographer acquires more experience, simply because there are few experienced producers.

Insert Table 1 about here

Table 2 presents the conditional logistic models we estimated to assess the probability of a specific cinematographer being hired. Figure 2 presents the marginal effects with 95% confidence intervals for the full model in Table 2 ("Project specific expertise").

Insert Table 2 about here

Insert Figure 2 about here

Table 3 presents the linear mixed models we estimated to evaluate performance of realized teams.

Insert Table 3 about here

Our first hypothesis stated that the overlap in expertise between a cinematographer and project stakeholder would have an inverted U-shaped relationship with the likelihood of a cinematographer being hired. This is not true for the overlap in expertise with the producer (β=-1.25, NS, square term: β =2.27, p<0.1). But it is the case for the overlap in expertise of the cinematographer with the director (β =4.36, p<0.01), square term: β =-3.55, p<0.01). Therefore, our first hypothesis is confirmed for the overlap in expertise between the cinematographer and the director.

Our hypothesis 2 stated that overlap in expertise between the cinematographer and the team members will have an inverted-U shape relationshop with team performance. We find evidence for an inverted U-shaped effect with the director (β =1.81, p<0.01, square term: β =-1.94, p<0.05) but not with the producer (β =-0.02, NS, square term: β =-0.03, NS). Therefore, our hypothesis 2 is partially supported for the relationship between the director and the cinematographer.

Our hypothesis 3 predicted that having project specific expertise with regard to genre would increase the cinematographer's likelihood of being hired. This turns out not to be the case, as we find a strong negative effect of a fit of the cinematographer's expertise with the movie genre (β =-0.68, p<0.01). This means that a cinematographer that has prior expertise in the genre of a movie is less likely to be hired for that movie than a cinematographer that has none. Therefore, our hypothesis 3 is not confirmed.

Our hypothesis 4 stated that project specific expertise of the cinematographer would have a positive effect on performance of the movie. We find evidence that indeed project specific expertise in terms of genre has a positive effect on performance (β =0.49, p<0.01). Therefore, our hypothesis 4 is supported.

DISCUSSION

Our study set out to explore the effects of expertise similarity as well as expertise fit on the likelihood of being hired in a knowledge intensive project based market. We also explore the effects of those constructs on the performance of the teams formed.

We elaborated our theoretical model building on prior team literature with the aim of exploring team formation as an antecedent of team composition. Surprisingly, while team composition has been a major research theme in the management literature, team formation has often been overlooked or identified with team composition. We highlight how incumbents might be tripping themselves up when hiring new team members as a result of the signals they rely upon to select individuals. This leads them to hire individuals who are similar to themselves and fail to hire the individuals that are the most appropriate for the project at hand.

We measured the overlap in terms of expertise between the cinematographer and the project stakeholders. We found that with the director there is an inverted-U relationship between the overlap in expertise and the likelihood of being hired. This is an indication that individuals who are too close in terms of expertise appear as not adding to the team skill set and therefore are not seen as strong contenders for a position. While individuals whose expertise is too different from the director's are more difficult to evaluate and the director probably perceives them as riskier choices, it means that the director will retain them less than the average for a position. However, the finding that we do not observe the same functional form for the relationship with the producer suggests a different process at play here, where the more overlap there is the more likely producers are to feel compelled to hire a cinematographer. One has to remark that the change in probability associated with similarity with the producer is small. This is in line with the producer being further removed from the set and therefore using different heuristics than directors to evaluate cinematographers. Not having to interact on set very closely with the cinematographer means that they do not perceive redundancy of expertise as a potential problem. This is further supported by the fact that we do not find any conclusive evidence that different dimensions of similarity between producers and cinematographers have an influence on performance.

Indeed, this inverted-U relationship holds for the similarity between the director and the cinematographer when looking at performance of the teams, but not for the relationship between the producer and the cinematographer. The director works very closely with the cinematographer on the set of the movie, while the producer has fewer dealings with the cinematographer once the production starts. This is an indication that on the set, in day-to-day work, some overlap in expertise facilitates the communication and execution between the director and the cinematographer, while no overlap makes exchange more difficult for lack of common references. On the other end of the spectrum, too much overlap might still have a

positive impact on the promptness of work but at the cost of creativity coming out of differing opinions and expertise. In other words, it is a situation in which too much agreement between individuals leads to work that is promptly executed but the absence of challenge to the dominant view leads to less creativity and therefore cripples performance of the teams on average.

The fit in terms of expertise has long been a studied dimension of teams. An entrepreneurial team will want to hire individuals whose skills complement and extend the ones they already possess in order to develop a better product or service. However, we find that in our setting, fit of expertise lowers the likelihood of being hired. But we still observe the positive effect of fit of expertise on performance.

This is surprising. It seems that project stakeholders overlook expertise fit when hiring. Probably the reason is that similarity in terms of expertise is a more salient dimension and overweighs the fit dimension in project stakeholders' decisions. However, as we have seen, similarity in terms of expertise is a double edge sword because individuals have to hit the right balance between too much and too little overlap. Whereas, the benefit of having a cinematographer with project specific expertise is strong when considering performance.

Among the control variables we used, one result strikes us as warranting comment. We measured similarity in terms of experience by measuring to what extent individuals' experiences are similar in terms of number of movies they have worked on. We found that incumbents have a tendency to hire people with either a lot more or a lot less experience than they have. We also found a smaller tendency for incumbents to hire people similar to themselves but this is much smaller than the tendency to hire people with different experience. Incumbents are however the least likely to hire individuals that have a number of experiences only moderately different from theirs. This is contrary to results of prior

literature which found that individuals tend to work with others with similar experience (Faulkner & Anderson, 1987). It seems that controlling for tenure and tenure similarity reveals that the positive association had more to do with the fact that individuals who start on the market together have a higher chance of collaborating than two randomly selected individuals, this is usually referred to as a cohort effect. This however is only true of individuals interacting closely on set and not of the more instrumental relationship between the producer and the cinematographer.

Discrepancies between the determinants of hiring and those of success

The main contribution of our paper is to highlight discrepancies between the signals incumbents rely upon to recruit new team members and the effect of the characteristics of those new team members on performance.

We focused on expertise overlap and project specific expertise to show that the heuristics used by incumbents might lead them to assemble sub-optimal teams.

By doing this, we overcome one of the limitations of the team composition literature that limits itself to the consequences of team composition on performance. We show that team formation, not only team composition, constrains team performance, because incumbents choose new team members based on criteria that do not lead to better team performance.

Our study fills an important gap and opens a new area for future research by highlighting that teams are plastic entities. Because they change over time, it is important to understand how team composition is likely to evolve as a result of the signals relied upon by team members searching for new additions to the team. As such, a better understanding of team formation processes will result in a better understanding of the drivers of team performance.

Limitations

Generazibility is one limitation of our study. It is true that the film industry is a specific context. However our findings open the black box of the team, showing that who in the team you are similar to does matter. These findings are relevant for any setting in which there is a need to form teams. For example, when an entrepreneur has to put a team together.

The relatively short time period covered by our data is another limitation, as we only observe matches on the market for 14 years. We have to reduce the panel further to use the first years of data to build our variables. In addition, we only have a limited set of control variables. This is partly compensated for by the inclusion of fixed effects for individual cinematographers, which control for unobserved characteristic of individuals. In addition, we ran robustness checks that yielded similar results.

Managerial implications

This study develops very actionable insights. The implications for managers are straightforward: natural bias when making decisions might lead to sub-optimal decisions. Managers should therefore be careful to keep their intuition in check and make sure that their positive evaluation of potential hires is sustained by more than the perception of fit that comes from similarity between them and the newcomer.

In short, managers need to be aware of the heuristics they use to make recruitment decisions and check that they are making the best decisions they can with the data at their disposal. Otherwise, they risk being their own worst enemies.

Conclusion

In this paper, we have shown how dynamic network information can be used to better understand team formation. We showed that the proximity of a potential new team member with strategic incumbents is essential in the hiring process, even when controlling for past experience and success.

We show how discrepancies between hiring heuristics and determinant of success in uncertain settings, leads project stakeholders to assemble suboptimal teams. In other words, project incumbents are tripping themselves up.

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TABLES

Table 1: Correlations

	Mean	S.d	1	2	3	4	5	6	7	8	9	10	11
1. Experience	2.72	3.96											
2. Tenure	4.95	3.78	0.50***										
3. Mean admissions	179739	335806	0.08***	0.14***									
4. Prior collaboration (producer)	0.04	0.25	0.01	0.00	0.00								
5. Prior collaboration (director)	0.06	0.37	0.00	0.00	0.00	0.00							
6. Experience homophily (producer)	0.52	0.27	-0.52***	-0.33***	-0.06***	-0.01	0.04***						
7. Experience homophily (director)	0.47	0.27	-0.17***	-0.07***	0.00	-0.08***	0.01	0.08***					
8. Tenure homophily (producer)	0.29	0.21	-0.05***	-0.06***	-0.02	0.01	0.03*	0.11***	0.02				
9. Tenure homophily (director)	0.30	0.22	-0.01	-0.01	0.01	0.02	0.00	0.00	0.02	0.10***			
10. Project specific expertise	0.66	0.47	0.24***	0.38***	0.14***	0.01	-0.01	-0.19***	0.00	0.02	0.06***		
11. Expertise overlap (producer)	0.07	0.14	0.09***	0.09***	0.00	0.01	-0.02	-0.05***	-0.02	0.04***	0.02	0.24***	
12. Expertise overlap (director)	0.03	0.10	0.05***	0.07***	0.00	-0.01	-0.01	-0.03**	-0.01	0.00	0.05***	0.10***	0.27***

Table 2: Conditional regression on the probability of a tie, 4 control cases for each realized tie.

	Controls	Experience homophily (squared)	Expertise overlap	Expertise overlap (squared)	Project specific expertise
Experience	0.219***	0.084***	0.083***	0.083***	0.087***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Tenure	-0.121***	-0.121***	-0.120***	-0.121***	-0.105***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)
Mean admissions	-0.341***	-0.311***	-0.327***	-0.331***	-0.295***
	(0.032)	(0.035)	(0.036)	(0.036)	(0.035)
Mean admissions (squared)	0.019***	0.017***	0.018***	0.018***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Prior collaboration (producer)	-0.482**	-0.507**	-0.514**	-0.502**	-0.506**
	(0.228)	(0.229)	(0.233)	(0.233)	(0.233)
Prior collaboration (director)	0.159	0.217	0.225	0.230	0.229
	(0.164)	(0.174)	(0.177)	(0.178)	(0.183)
Prior collaboration (producer, squared)	0.124*	0.123**	0.125**	0.120*	0.118*
	(0.064)	(0.061)	(0.062)	(0.063)	(0.062)
Prior collaboration (director, squared)	-0.051	-0.056	-0.059	-0.061	-0.064
	(0.045)	(0.046)	(0.048)	(0.048)	(0.051)
Tenure homophily (producer)	-0.091	-0.079	-0.070	-0.050	-0.006
	(0.174)	(0.174)	(0.173)	(0.173)	(0.176)
Tenure homophily (director)	0.317*	0.610***	0.584***	0.542***	0.535***
	(0.179)	(0.174)	(0.174)	(0.175)	(0.175)
Experience homophily (producer)	-0.760***	-3.298***	-3.385***	-3.413***	-3.257***
	(0.154)	(0.566)	(0.569)	(0.571)	(0.573)
Experience homophily (director)	-0.107	-10.795***	-10.775***	-10.761***	-10.651***
	(0.174)	(0.713)	(0.711)	(0.715)	(0.724)
Experience homophily (producer, squared)		2.562***	2.635***	2.673***	2.551***
		(0.519)	(0.522)	(0.523)	(0.524)
Experience homophily (director, squared)		8.296***	8.280***	8.273***	8.169***
		(0.532)	(0.533)	(0.534)	(0.539)
Expertise overlap (producer)			0.300	-1.623	-1.252
			(0.474)	(1.106)	(1.142)
Expertise overlap (director)			1.308***	3.273***	4.360***
			(0.400)	(0.906)	(0.910)
Expertise overlap (producer, squared)				2.650**	2.269*
				(1.298)	(1.346)
Expertise overlap (director, squared)				-2.805**	-3.553***
				(1.222)	(1.228)
Project specific expertise					-0.682***
					(0.100)
AIC	4160	3823	3810	3806	3765
R^2	0.133	0.168	0.170	0.171	0.175
Max. R^2	0.475	0.475	0.475	0.475	0.475
Num. events	1651	1651	1651	1651	1651
Num. obs.	8255	8255	8255	8255	8255
Missings	0	0	0	0	0

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Linear mixed models on the performance of teams

	Controls	Experience homophily (squared)	Expertise overlap	Expertise overlap (squared)	Project specific expertise
Constant	3.495***	3.520***	3.548***	3.524***	3.530***
	(0.139)	(0.193)	(0.193)	(0.193)	(0.191)
Experience	0.063***	0.063***	0.062***	0.061***	0.062***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
Tenure	-0.034*	-0.034*	-0.033*	-0.036*	-0.044**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Mean admissions	0.146***	0.149***	0.124**	0.121**	0.082
	(0.052)	(0.053)	(0.053)	(0.053)	(0.054)
Mean admissions (squared)	-0.009**	-0.009**	-0.008*	-0.008*	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Prior collaboration (producer)	-0.047	-0.044	-0.080	-0.114	-0.125
	(0.290)	(0.291)	(0.290)	(0.289)	(0.287)
Prior collaboration (director)	0.323	0.322	0.360*	0.369*	0.383*
	(0.207)	(0.209)	(0.209)	(0.209)	(0.207)
Prior collaboration (producer, squared)	0.041	0.040	0.049	0.057	0.057
	(0.087)	(0.087)	(0.087)	(0.087)	(0.086)
Prior collaboration (director, squared)	-0.150**	-0.150**	-0.155**	-0.156**	-0.157**
	(0.062)	(0.063)	(0.063)	(0.063)	(0.062)
Tenure homophily (producer)	-0.039	-0.037	-0.049	-0.032	0.015
	(0.165)	(0.165)	(0.164)	(0.164)	(0.163)
Tenure homophily (director)	0.068	0.065	0.039	0.003	-0.009
	(0.168)	(0.169)	(0.169)	(0.169)	(0.168)
Experience homophily (producer)	0.385***	0.174	0.042	0.044	0.021
	(0.131)	(0.507)	(0.506)	(0.505)	(0.502)
Experience homophily (director)	0.110	0.136	0.113	0.232	0.110
	(0.150)	(0.627)	(0.624)	(0.624)	(0.621)
Experience homophily (producer, squared)		0.212	0.329	0.323	0.309
		(0.491)	(0.490)	(0.489)	(0.487)
Experience homophily (director, squared)		-0.021	0.004	-0.078	0.035
		(0.512)	(0.510)	(0.510)	(0.507)
Expertise overlap (producer)			-0.172	0.278	-0.023
			(0.341)	(0.723)	(0.721)
Expertise overlap (director)			0.881***	1.997***	1.814***
			(0.263)	(0.544)	(0.542)
Expertise overlap (producer, squared)				-0.349	-0.030
				(1.147)	(1.141)
Expertise overlap (director, squared)				-2.056**	-1.936**
				(0.933)	(0.927)
Project specific expertise					0.493***
					(0.116)
AIC	6070	6073	6067	6061	6047
BIC	6152	6165	6170	6174	6166
Log Likelihood	-3020	-3020	-3015	-3009	-3002
Deviance	6040	6039	6029	6019	6003
Num. obs.	1651	1651	1651	1651	1651
Num. groups: cinematographer	872	872	872	872	872
Variance: cinematographer (constant)	1.190	1.193	1.216	1.226	1.233
Variance: Residual	1.422	1.423	1.401	1.390	1.367

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

FIGURES

Figure 1: Team formation as a process preceding team composition

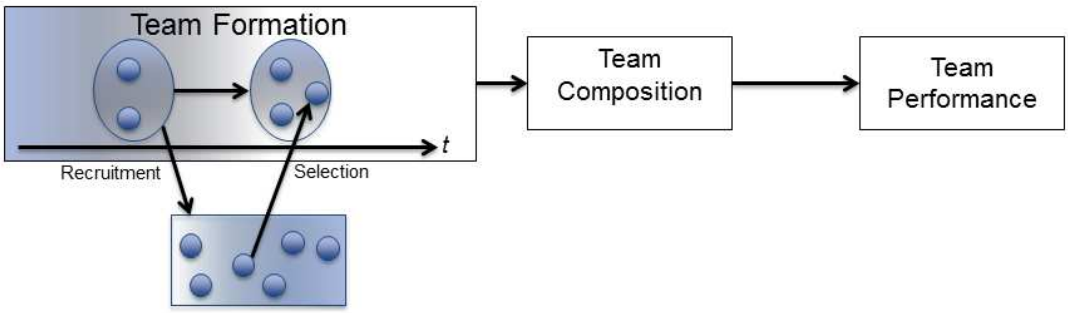

Figure 2: Marginal effects and 95% confidence interval