The Company They Keep: How Human Brand Managers and Their Social Networks Shape Job Market Outcomes

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Abstract

Individuals, as human brands, “market themselves” to become appealing to prospective parties, such as employers. Yet the responsibility of marketing a human brand rarely falls on an individual alone: mentors, agents, academic advisors, and other individuals actively market the human brand as well. We introduce the term “human brand manager” to describe these individuals, and propose that their social networks play an important role in the success of the human brands they manage. Such networks may be actively used to influence the human brand manager’s contacts or may also serve as an additional signaling mechanism for the human brands. This proposition is tested in the context of the marketing job market. We uncover unobservable communities of academic advisors using a community detection algorithm on placement and coauthoring patterns. When advisors belong to dense communities, candidates can benefit from additional salary gains, up to $23,419.03 in the case of placement communities and $15,149.58 in the case of coauthorship communities, after controlling for candidate and departmental quality. This shows that human brand managers’ membership in diverse social networks shape job market outcomes, and that their role in signaling value is sometimes superior to the human brand’s quality.

Keywords: Social networks; Human brands; Research productivity; Coauthorship, Job market.

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1. Introduction

A product's attributes serve as cues that consumers interpret to assess product quality (Rao and Monroe 1988). Analogously, human brands, such as celebrities (Fournier 2010), political candidates (Hoegg and Lewis 2011), and artists (Moulard et al. 2014) possess attributes, known as human brand cues, which signal the human brand's quality. Human brand cues have been shown to influence the job market success of doctoral candidates (e.g., Zamudio et al. 2013) and the attitudes towards an artist and his artwork (Moulard et al. 2014), among other outcomes.

Human brands are often co-managed by individuals such as agents, middlemen, or advisors who plan and coordinate a branding strategy for the human brand to effectively signal the human brand's quality. For example, boxing promoters develop mentorship relationships with their fighters and carefully develop their career by leveraging their social influence with television networks and other promoters (Bishop 2011). Similarly, a doctoral candidate's advisor usually guides the candidate's choice of a marketable dissertation topic. We call these individuals "human brand managers." Most research implicitly assumes that human brand cues are actively managed by the human brand alone; human brand managers are only conceptualized as a signaling device whose own human brand cues provide additional extrinsic cues to the human brand(s) they manage (e.g. Close et al. 2011).

This conceptualization of human brand managers—as signaling devices, not active market participants—obscures a potentially important aspect of human brand managers: their social networks. Human brand managers may use their social networks to influence the market outcomes of the human brands they manage by obtaining interviews, negotiating contract terms, and so forth. Additionally, the human brand manager's membership in various social networks may constitute an additional quality signal for the managed human brand as well. For example, an advisor may secure interviews for his or her candidate by contacting members of his coauthorship network; in addition, a hiring academic department's positive perceptions of that advisor's coauthorship network may help the candidate's success on the job market. Thus, both the human brand manager's active promotion of the human brand using his/her social networks and others' perception of those networks may impact the managed human brand's job market outcomes.

As such, we empirically investigate whether a human brand manager's membership in various social networks influences market outcomes for the managed human brand in the context of the entry-level marketing job market. Specifically, we (1) uncover two types of advisor networks—placement and coauthorship communities—and (2) assess the effects of advisors' membership in these communities on doctoral candidates' salary, campus visit offers, and AMA interviews. We show that ignoring the effects of advisors' community memberships overestimates the effects of several candidate, advisor, and market characteristics, and that membership in different networks has different effects on placement success.

Our research makes theoretical, substantive, and methodological contributions. Concerning theoretical contributions, we conceptualize the human brand manager and empirically verify its role on the success of the managed human brand. Thus, we add to the literature on human brands (e.g. Thomson 2006; Close, Moulard and Monroe 2011), specifically to recent research on the human brand manager's importance to the managed human brand's success (Parmentier et al. 2013). Additionally, these findings extend research on social networks, which have found that an actor's social networks influence outcomes for that same actor (e.g., Swaminathan and Moorman 2009; Barbulescu 2014; Gonzalez, Claro, and Palmatier 2014). We show that network effects extend to actors who do not belong to a network yet are affiliated with a network member. This finding may be relevant for research using theories such as signaling, social capital, and the resource-based view of the firm.

Substantively, we extend recent empirical work on the marketing job market. Previous studies have found that candidates' human brand cues influence job market success (Close et al. 2011; Zamudio et al. 2013). Using data on marketing scholar coauthorships (Goldenberg et al. 2010) and historical placement data, we uncover unobserved advisor networks known as communities (Newman 2004). We find that advisors' membership in these communities strongly influence candidates' job market outcomes, sometimes more so than the candidate's own human brand cues, and we estimate which networks are most impactful. Thus, we show that including human brand managers' networks when investigating job market outcomes increases explanatory power and reduces potential biases.

Methodologically, we introduce community detection into the marketing literature. Unlike other approaches, this state-of-the-art community detection algorithm applied in our study (Blondel et al. 2008) accurately detects actor clusters in massive social networks while remaining computationally feasible. This advantage is highly relevant given a growing interest in big data analysis (e.g. Lee and Bradlow 2011, Netzer et al. 2012).

The rest of the article is organized as follows. Section 2 discusses our research background and conceptualizes the human brand manager; Section 3 reviews community detection in social networks; Section 4 discusses the data used in the study and our empirical approach; Section 5 presents our results; and Section 6 discusses our results and presents implications for researchers and market participants.

2. Research Background

2.1 Human brands

While the concept of "brand" often refers to goods and services, any person who is the subject of marketing communication efforts can be considered a brand (Thomson 2006), and include celebrities (Luo et al. 2010), visual artists (Moulard et al. 2014), political candidates (Hoegg and Lewis 2011), and scholars (Close et al. 2011; Zamudio et al. 2013). Much of the previous work on human brands has focused on identifying human brand cues that influence how interested parties perceive the human brand. For instance, Luo et al. (2010) show that a celebrity's likeability rating is positively influenced by factors such as the celebrity's film ratings and total award nominations, and Hoegg and Lewis (2011) report that political candidates are most preferred and voted for when their traits match those of their political party.

One aspect of the human brand not fully examined is the "human brand manager," that is, the person partially responsible for managing the human brand (along with the human brand himself or herself). Close et al. (2011) and Zamudio et al. (2013) acknowledge the role of the human brand manager, but neither considers the active management that he or she may offer; rather, they suggest that the human brand manager serves as a quality cue for the managed human brand. And while Parmentier et al. (2013) show that fashion model agents are highly influential in establishing a model's brand positioning, their study stops short of assessing the magnitude of such influence on the model's success. Further, the human brand manager has not been fully conceptualized in these previous studies.

2.2. Human Brand Managers and their Networks

We define a human brand manager as an individual that plans and coordinates the marketing and branding activities of a human brand.[1] Whereas many individuals may influence these activities, the human brand manager is the primary influencer and may be hired to perform such duties. While an economic exchange may be required, some type of social reciprocation may be the norm in certain contexts. For instance, a doctoral candidate may be expected to include his or her dissertation advisor as a co-author on a manuscript based on the doctoral candidate's dissertation.

Although one could think that managing a human brand is similar to managing a product brand, a human brand manager is different from a product brand manager for three reasons. First, the human brand, unlike a product, has agency and is thus never under total control of the human brand manager. For example, a celebrity or politician may choose not to heed his or her agent's advice in speaking with the media regarding a contentious subject. Second, while product brand managers manage product brands, human brand managers "co-manage" alongside their managed human brands. As such, their objectives may diverge. For instance, an advisor may believe that his or her job candidate would best fit at a research school, whereas the candidate may prefer a balanced school. Third, in the absence of collusion, the social relationships between product brand managers should not be expected to influence their product's success; yet, many examples exist of human brand managers marketing the human brands they manage to other human brand managers within their social network. In China, for instance, a mentoring relationship for career success involves a promise of *Guanxi*, or network ties (Bozionelos and Wang 2006). The human

[1]Throughout our study, we do not distinguish the human and the human brand. In other words, we assume that whichever activity a human performs ultimately influences the perceived quality of his or her human brand. However, a celebrity's public image may be highly distinct from his or her actual private self, as is the case for Stephen Colbert (McGrath 2012). Investigating the circumstances under which the human brand's image should be distinguished from the human itself may be a fruitful avenue for further research.

brand manager's networks thus provide positive social capital externalities for the managed human brand in that he or she can benefit from access to senior brokers (Galunic et al. 2012).

Human brand managers perform several functions. First, they select which human brands to manage (or not manage). For instance, due to commitments with other athletes, famous sports agents may reject signing a particular additional athlete. Second, similar to how product managers engage in new product development, human brand managers engage in human brand development, investing multiple resources to nurture their managed human brand. For example, academic advisors spend time and effort editing their doctoral students' dissertation and may use their own resources to fund the student's data collection. Third, human brand managers guide their managed human brands concerning decisions that may signal their quality. Academic advisors may suggest, for instance, that a doctoral job candidate submit a manuscript to a top marketing journal to signal the candidate's quality or aspirations.

Among the functions that human brand managers perform for their managed human brands, human brand development seems most critical – specifically, assistance in career success (Parmentier et al. 2013). Previous studies recognize this assistance, but conceptualize it as stemming from a co-branding arrangement: a job candidate, by virtue of having a specific advisor, obtains an additional, extrinsic human brand cue to signal his or her quality (Close et al. 2011; Zamudio et al. 2013). However, as discussed previously, the role of human brand managers' social networks has not been considered concerning human brand development and career success. We propose that a human brand manager's social network may positively impact job market success for the managed human brand for two reasons. The first reason is networking: Human brand managers may actively "market" their managed human brand by obtaining interviews and other exposure opportunities by communicating with others within their social networks. The second reason is signaling: Although a human brand manager may not *necessarily* have an active role in marketing the managed human brand, others' perception of the social networks the human brand manager belongs to, and his or her influence therein, may represent an additional, extrinsic brand cue that the human brand can use to bolster his own quality. In either case, the human brand may enjoy a more successful job market outcome via his or her association with the human brand manager and, thus, his or her social network.

2.3. Human Brand Management in the Marketing Market

We empirically test the above proposition in the context of the entry-level marketing job market (henceforth "marketing market"). In this market, career success begins with the transition from doctoral candidate to assistant professor. Specifically, we measure "success" as the number of interviews, campus visits, and salary obtained by a candidate in the marketing market. From a social capital theory standpoint, career success is determined by the social resources available to a candidate via his or her social network —access to information, access to resources, and career sponsorship (Seibert et al. 2001). From this perspective, advisors should be expected to strongly influence the job market success of job candidates. Yet past research on their effect on job market outcomes suggests the opposite: the "advisor effect" is rather small (Close et al. 2011; Zamudio et al. 2013). As discussed above, this is because the role of the human brand manager as an active market player has not been conceptualized in the literature. To recast the role of advisors in the marketing job market, the social networks they may participate in must be explored.

Marketing scholars engage in a wide variety of social activities - coauthoring on research projects (Hoffman and Holbrook 1993), attending and presenting research at conferences (Morlacchi et al. 2005), organizing task forces in discipline-wide institutions (AMA Task Force

1988), evaluating the process of scientific inquiry (Lehmann et al. 2011), determining research priorities (Keller and Lehmann 2006), friendship, and so forth. This social interaction often spans departments, academic disciplines, interest areas and geographic regions (e.g., Tellis et al. 1999; Theoharakis and Hirst 2002), and implies that the scholar is an active participant in networks of co-authors (scholars with whom research or teaching is produced) and perhaps networks of friends (scholars with whom there is a collegial interaction, but no research or teaching is produced). Apart from being essential for the scholar's teaching and research duties, interactions with other scholars provide for a social relationship that can be leveraged for resources (Crane 1969).

Empirically, identifying networks such as the above necessitates archival records on ties among scholars. In the case of co-authorship, with N scholars in a field at some cross-section of time, these ties can be represented on a $N \times N$ matrix, A, where each cell a_{ij} holds the number of times scholars i and j have published together. Alternatively, one can assign $a_{ij} = 1$ if scholars i and j have published together, regardless of how often. In the former case, A would be called a *weighted* matrix; in the latter, A would be called an *unweighted* matrix. Other types of networks based on archival information, such as citations, can also be used to form similar matrices.

Whereas some ties among scholars, such as coauthorships, are rather visible, others are subtler. For example, scholars that do not coauthors with each other may attend a certain conference every year, and groups of advisors may place their students in the same university or *co-place*. In both cases, although scholars are not directly connected, as in the case of co-authorship, they are *affiliated* by virtue of attending the same events or placing in the same universities; an affiliation network is represented by a $N \times N$ matrix, where each cell a_{ij} holds the number of times scholars i and j coincided together in the same event.

3. Community Detection in Social Networks

Recent advances in social network analysis allows groups of actors strongly connected to each other and sparsely connected across groups or "communities" to be endogenously discovered in the network. We apply one of these algorithms in this article – the Blondel et al. (2008) algorithm. To our knowledge, this is the first application of such a community detection algorithm in the marketing literature. We present an overview of community detection in social networks and a discussion of the Blondel et al. (2008) algorithm next.

4.1.Network Communities and Modularity

Among the techniques to detect closely related actors in a social network, community-detection algorithms are most recent (e.g., Newman 2006; Blondel et al. 2008). These algorithms place emphasis on detecting communities within large networks efficiently and according to a metric known as modularity (denoted as Q). This metric measures the density of the links within the communities found as compared to the expected value of this density if random connections between actors occurred instead. A modularity of 0 implies that the number of ties within communities is no better than random, whereas a modularity of 1 implies strong community structure. Values above 0.3 indicate a good community solution (Newman and Girvan 2004). The modularity metric for weighted networks can be computed as (Blondel et al. 2008):

$$Q = \frac{1}{2m} \sum\nolimits_{i,j} \left[a_{ij} - \frac{k_i k_j}{2m} \right] \delta(i,j) \tag{1}$$

In Equation 1, m represents the total number of ties among communities in the network, a_{ij} is the weight of the tie among communities i and j contained in matrix A, a_{ii} represents the weight of the ties within community i, $k_i = \sum_j a_{ij}$ is the sum of all ties incident to community i, and δ is an indicator function which takes the value of 1 if $i = j$ and 0 otherwise.

In this article, we apply a state-of-the-art community detection algorithm known as the Louvain algorithm (Blondel et al. 2008). The algorithm has several appealing features for marketing scholars interested in social network analysis. First, the algorithm can handle networks of millions of actors in a very short timespan. Second, the algorithm is insensitive to starting values. Third, the method allows for a very thorough network exploration and thus can detect small communities that other techniques would fail to identify (Fortunato and Barthelemy 2007).

The main idea behind the Louvain algorithm is that by moving actors from community to community, improvements in modularity may be observed. Consequently, one can improve a community detection solution by finding actor moves that increase modularity. The algorithm consists of two steps and a reiteration until convergence, as discussed below.

Step 1. First, each of the N actors that form the social network under examination is assumed to be a community in itself. Therefore, for initialization, there are as many communities as there are actors. For each actor i, the potential modularity gain from adding actor i to each neighbor j into a proposed community C is evaluated in terms of modularity gain, that is,

$$\Delta Q = \left[\frac{a_{in} + 2k_{i,in}}{2m} - \left(\frac{a_{tot} + k_i}{2m}\right)^2\right] - \left[\frac{a_{in}}{2m} - \left(\frac{a_{tot}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right] \tag{2}$$

where a_{in} is the sum of the weights of the ties within proposed community C, a_{tot} is the sum of the weight of the ties incident to all actors within proposed community C, and $k_{i,in}$ is the sum of the weights of the ties from actor i to all other actors within proposed community C. All moves of i to adjacent communities j are evaluated and then, if any gain in modularity can be achieved, the movement is made and C becomes a new community. For computational feasibility, a move may be made only if the gain in modularity exceeds a pre-specified threshold.

Step 2. Once an initial set of communities has been found, the algorithm uses them to form a new social network where each community above becomes a synthetic actor. Thus, the size of the new network is smaller: for instance, if after Step 1 only one new community consisting of two actors is formed, the new network will be of size $(N-1)\times(N-1)$ because the two actors are now merged into a new synthetic actor – a community. Weights among communities are computed as the sum of the weight of the ties among their members so that the new, reduced network preserves the modularity of the original (Arenas et al. 2007).

Iteration. Steps 1 and 2 are known as a "pass". The algorithm iterates pass by pass to form communities of higher hierarchy. The algorithm stops once no more changes can be made to the community structure; a modularity maximum is then said to be attained.

4. Data

4.1. Variables

We used two main datasets in this study. The first one consists of 324 marketing job candidates and 211 hiring departments placed by 239 advisors during 2003-2007, as in Close et al. (2011). We call this dataset the *placement dataset.* Additional placements and covariates were obtained from extensive Internet searches and marketing faculty directories. The second one is Goldenberg et al.'s (2010) data on marketing journal coauthorships from 1973-2007. We call this dataset the *coauthorship dataset.* Table 1 summarizes the placement variables, along with descriptive statistics.

Insert Table 1 about here

The first set of variables in Table 1 includes job market metrics. The 9-month adjusted salary (which we refer to as "salary") is the sum of a candidate's base 9-month salary offer, plus summer support. Salaries are reported in 2007 dollars to account for inflation. Notice that for application letters, interviews, and campus visits, the minimum is zero. This is because four candidates reported these minimums, presumably because they were hired outside the market. However, these observations still contain valuable information in the form of salaries and advisors' identities, and were kept for analysis.

The second set of variables addresses characteristics of each candidate's degree-granting department. We gathered each department's number of publications in the *Journal of Marketing*, *Journal of Marketing Research*, *Journal of Consumer Research* and *Marketing Science* journals up until the year when they were observed placing or hiring. On average, the degree-granting departments in our dataset produced 13.47 such publications. The majority of these departments are public (80%), and slightly less than half (41%) are top-ranked, where this ranking status was assigned using UT Dallas research rankings and Financial Times MBA rankings (Zamudio et al. 2013). Finally, we included the cost of living index of the city where each degree-granting department is located.

The third set of variables concerns job candidate's human brand cues. The field of research distribution leans towards consumer behavior (CB) candidates. 48% of the candidates defended their proposal with data and 24% without data, as compared to the remaining 28% of candidates who had not defended their proposal yet. In regards to research productivity, we gathered candidates' research activity in conference proceedings and multiple journals. We sought to develop a list of "A-level" journals representative of marketing scholars' preferences across departments. We used the composite journal rankings in Steward and Lewis (2010) to determine such a list, which we call "A-level", and includes six journals: the *Journal of Consumer Research, Journal of Marketing, Journal of Marketing Research, Journal of Retailing, Journal of the Academy of Marketing Science,* and *Marketing Science.* We also defined "B-level" journals to include all others journals within marketing. Conference proceedings are most common (4.30 on average), followed by B-level journal publications (0.73 on average) and A-level journals (0.2 on average). The amount of submissions and papers past first review in both A-level and B-level journals are similar in magnitude, yet A-level publications are far less, which hints at the exclusivity of these outlets. 78% of candidates attended the Sheth Consortium.

The last set of variables concerns advisors' human brand cues. Top publications average at 9.97 per advisor. Advisors also had 6.48 past dissertations advised, on average. We also describe advisors using their membership in social communities in the forthcoming sections.

4.2. Approach to Analysis

We are interested in assessing the role of job market metrics, department, advisor and candidate characteristics, as well as advisors' membership in coauthorship and placement communities, on multiple job market outcomes – AMA interviews, campus visits offered, and salary. Whereas the dependency of one outcome on the other may be partially addressed by including previous outcomes as covariates (Close et al. 2011), the unobserved portion of these outcomes could be correlated. To address this possibility, we apply a Seemingly Unrelated Regression (SUR) model consisting of three equations – one for each job market outcome.

5. Results

In this section, we first discuss the members and characteristics of the advisor communities uncovered with the Louvain algorithm. We then investigate whether being advised by a member of one of these communities influences different job market outcomes.

5.1 Advisor Communities – Coauthorship

The first type of community we uncovered is that of advisors densely connected to each other by virtue of their coauthorship using the Goldenberg et al. (2010) dataset. The dataset includes all known pairs of scholars that coauthored in 49 leading Marketing journals from 1973 to 2007. 30,897 scholars are present in the dataset. We formed a weighted square matrix of 54,066 unique pairs of coauthors during the 34 years in the investigated time period.

The weights of the matrix are computed as follows. The Goldenberg et al. (2010) "Links" dataset contains information on the 54,066 pairs of coauthors. These are the basis for community detection. For each pair, the dataset contains the number of times the pair coauthored, broken by journal. Because the data is at the pair level, one can know how many times two scholars coauthored in a particular journal together, but not how many publications a particular scholar had in that journal. For example, if scholars A, B and C published five times in *Marketing Science,* scholar A would have five coauthorships in *Marketing Science* with scholar B, and five with scholar C, for a total of 10 coauthorships. Therefore, the weight assigned to each unique pair of coauthors is the number of times they coauthored in different journals. The coauthorship community analysis will report average statistics based on number of coauthorships, not number of publications.

We applied the Louvain algorithm to the coauthorship matrix above. 3,435 coauthorship communities were found. Among these, 258 have more than 5 members and 96 more than 10 members. Despite the sparseness of these communities, the modularity of the solution, 0.84, implies a remarkably good community structure (Newman 2004).

In our placement dataset, 33 coauthorship communities are represented by advisors present in that dataset. 15 of these communities have more than 5 members represented in the data. We will analyze the aggregate, community-level characteristics of the advisors in the placement dataset who belong to these 15 co-authorship communities in what follows. Table 2 details their members and aggregate descriptive statistics.

Insert Table 2 about here

As shown in Table 2, only one co-authorship community is represented by more than 40 advisors, and 7 communities have less than 10 members represented in our placement data. The average level of influence (i.e. Eigenvector centrality) in these communities ranges from 0.01 to 0.25, and the percentage of coauthorships across journals is also quite varied. Higher influence is associated with scholars who coauthor in top marketing journals (r=.414, p<.01), with the opposite being true for other marketing (r=-.358, p<.01) and non-marketing journals (r=-.203, p<.01) using the categories defined in Zamudio et al. (2013).

We define a scholar's "research inactivity" as the years elapsed since the scholar's last publication. Research inactivity is negatively related to influence (r=-.251, p<.01) and number of papers written (r=-.344, p<.01). Research activity has not been addressed in previous literature, and our results show that it may hamper more than one research metric.

There is also heterogeneity in fields of research. The most represented advisors are CB scholars, most communities do not have modelers, and five communities feature a majority of strategy scholars. Interestingly, although CB and strategy scholars compose most of the top coauthorship communities, influence is more strongly associated with modeling scholars (mean influence difference vs. CB and strategy= .122, t=3.87, p=<.01).

5.2. Advisor Communities - Placement

The second type of community uncovered is that of advisors connected to each other by co-placement. That is, if two advisors placed at the same hiring department, regardless of the year, we consider them to be connected due to co-placement. We constructed an unweighted square matrix of 321 co-placements among the 231 advisors in the placement dataset. We use an unweighted matrix because no two advisors co-placed in the same department more than once.

The final solution exhibited a modularity of 0.89, which is remarkable considering that advisors in the network are very sparsely connected. Fig. 1 presents a visual representation of the community solution, including the names of the advisors within each community found in our placement dataset. Larger nodes indicate a larger Eigenvector centrality within the co-placement network, and colors represent membership in the different placement communities uncovered.

Insert Figure 1 about here

Forty-three placement communities were uncovered. Among these, 26 contain only two advisors, who placed 63 candidates (19.09% of total); 7 communities contain three advisors, who placed 31 candidates (9.39% of total); 10 communities contain more than three advisors, who placed 167 candidates (41.21% of total); the remaining 50 advisors were not associated with any community and placed 100 candidates (30.3% of total). In the following, we will examine the characteristics of the 10 communities which contain more than three advisors, as these constitute larger social structures which more closely resemble personal communities (Wellman et al. 1997). Table 3 lists the members of the 10 largest placement communities which appear in our dataset along with aggregate descriptive statistics.

Insert Table 3 about here

As Table 3 shows, there is also considerable heterogeneity within each community. There is no community with a majority of modelers although these scholars seem to be perceived differently when competing in the entry-level job market (Zamudio et al. 2013). The largest percentage of advisors comes from the CB field, with 8 communities having a majority of CB members. Only one community holds a majority of strategy scholars, and one community's majority is evenly divided among CB and modeling scholars.

There is also variation regarding advisors' research productivity and experience in chairing doctoral candidates. Advisors with the most experience are those with a higher number of top publications on average. Finally, it is critical to mention that there is a consistent pattern of placements among the members of each community, which lends credence to our community solution. In all but three communities, more than half of the placements were in the same hiring department. Community 7 is the densest case, with 85.71% of placements in Central Florida.

6.3. Departmental-Level Communities

In addition to advisor communities, department communities may also influence the market. In other words, whether advisor connections, departmental connections irrespective of the advisors, or both influence marketing outcomes is a testable proposition. To this end, we applied the Louvain algorithm to a supplementary dataset of 965 placements among 117 degree-granting departments and 352 hiring departments from 1997 to 2007. This resulted in 11 department communities. In our analysis, we will control for whether the departments involved in a placement belong to the same community.

6.4. The Effect of Human Brand Manager Communities on Market Outcomes

After discovering and characterizing coauthorship and placement advisor communities in marketing academia, we now assess the effect of advisors' membership in these communities in their job candidate's market outcomes. The results of our SUR model are shown in Table 4. All effects are simultaneously estimated with no multicollinearity issues (Mean VIF = 1.84).

Insert Table 4 about here

In Table 4, covariates are grouped into different categories. The first category includes job market outcomes. These covariates were added to determine if the job market process is a “self-fulfilling prophecy” in that a large number of interviews may lead to a commensurate number of campus visits offered, and so on. We find that performance in the latest stage of the job market significantly influences the next: only the number of job offers a job candidate received influence salary, only AMA interviews influence visits offered, and so on. These results are economically important. For each additional job offer received, a job candidate can expect his or her salary to increase by $1,785.99. In addition, a candidate can expect to convert one campus visit for approximately five interviews. Furthermore, for every thirteen application letters sent, candidates should expect an additional AMA interview.

The second category of covariates includes degree-granting department’s characteristics. Job candidates from top-ranked degree-granting departments can expect a salary $10,239.61 higher, and 1.43 extra campus visits offered than other candidates. Interestingly, a larger average number of top publications translates into less campus visits. However, the average of this covariate is only 13.47, which implies an expected loss of .674 interviews, which is economically unimportant. Finally, whether the departments involved in a placement come from the same departmental-level community has no bearing on marketing outcomes. This means that the effects of advisor communities found in what follows should be interpreted after controlling for this potential confound.

The third category of covariates includes candidate’s characteristics. Modelers reap consistently positive benefits in the market (with $8,626.40 additional salary, 1.07 additional campus visits obtained, and 2.98 additional interviews obtained on average). Whether a candidate has a dissertation proposal defended with data represents an expected gain of $8,626.40 over candidates with less-developed dissertations. However, at the interview stage, proposals defended *without* data imply an additional 2.53 AMA interviews. This may be because hiring departments at the interview stage only cursorily examine dissertation topics and have not yet fully vetted the candidate's dissertation and/or job market paper.

Regarding research productivity and honors, we find that each proceedings, B-level and A-level publications increase expected salary by $639.79, $1,678.64, and $4,834.99 respectively. Interestingly, proceedings and A-level publications are also conducive to a higher number of campus visits offered, but neither influences the interview stage: only A-level articles *past first review* have an effect, a finding consistent with previous literature (Close et al. 2011). Finally, Sheth Consortium attendance significantly increases expected salary ($4,081.24), despite the fact that most students in our sample attended the Consortium.

Advisors can influence candidates' market outcomes in two ways. As discussed before, previous research suggests that advisors can be used as a signaling device via their characteristics. Our results are consistent with this assertion to some extent: for example, although an advisor's average dissertations chaired negatively impacts salary by $394.17, the advisor's number of top publications positively impacts salary by $577.70. In addition, the effect of advisors' Eigenvector centrality of coauthorship (that is, the influence they exert in the coauthorship network as a whole) impacts interviews obtained only, such that an advisor with average coauthorship influence (.12) can generate 1.62 additional interviews for the candidate.

The fourth category of covariates includes advisor's membership in coauthorship and placement communities. We estimate the effect that the 15 largest coauthorship communities and the 10 largest placement communities have on job market outcomes. Because every advisor in our dataset is a member of some coauthorship community, one of these (C8) is kept as benchmark. In the case of placement communities, because 50 advisors were not associated with any, the results should be interpreted with respect to these advisors. Fixed effects for smaller communities were added as controls, except for four small coauthorship communities (each with three members) that were removed due to multicollinearity.

Among the 15 largest coauthorship communities, five (33.3%) significantly influence salaries. On average, the expected salary gain from coauthorship community membership across communities with statistically significant effects ($p<.05$) is $12,019.59. If a job candidate's advisor belongs to communities C1, C3, C5, C11 or C12, the minimum increase in expected salary is $8,082.54 (C5) and the largest is $15,149.58 (C12). The smallest (largest) gain above represents 1.67 (3.13) times the gain from a candidate's A-publication and 4.81 (9.02) times the gain from a candidate's B-publication. However, there is only one effect for visits offered (C5, 1.82 additional visits) and no effects at the interview level.

Among the 10 largest placement communities, 6 of them (60%) significantly influence salary. These are communities P1, P2, P3, P5, P8, and P10. The expected salary gain across statistically significant placement communities is $19,936.59 ($p<.05$)[2]. These effects are larger than coauthorship community effects. The minimum expected salary increase is $7,642.50 (P2) and the largest is $23,419.03 (P10). The smallest (largest) placement community effect are equivalent to 1.58 (4.84) times the salary gain from an A-publication and 4.55 (13.95) times the gain from a B-publication. As to campus visits, one effect is positive (P10, 3.47 additional

[2] We also applied the Louvain algorithm to an unweighted co-authorship matrix with each cell recording a binary value: 1 if two advisors coauthored at least once, and zero otherwise. We find that the results from using the resulting coauthorship communities are qualitatively similar, namely, that coauthorship and placement communities both influence job market outcomes and placement communities have a stronger influence.

interviews) yet one is negative[3] (P1, 1.48 less campus visits). One placement community positively influences interviews as well (P3, 6.51 additional interviews).

There is the possibility of another important source of variation: whether the advisor is related to the hiring department by virtue of being a former Ph.D. student or professor. To test this conjecture, we collected the full study and employment history (including visiting positions) of 214 advisors in our dataset (92.64% of total). Among these, only 7 placed a student in their degree-granting department, and only 4 in a department where they were previously employed. Because this variation is minimal, previous relations between the advisor and the hiring department are most likely not a concern (Gonzalez et al. 2014). Thus, this source of variation was not included in our SUR specification.

A Breusch-Pagan test of independence for our SUR analysis indicates that the outcome equations are independent ($\chi^2 = 0.21, p = 0.98$). Because of this, we performed hierarchical regression analysis on the three equations separately to determine whether the gains in explanatory power from adding each covariate group are significant. Results are shown in Table 5. The first group (job market metrics) is always significant and thus omitted from the table.

Insert Table 5 about here

Table 5 shows that co-authorship and placement communities substantially contribute to explain every market outcome. Surprisingly, these two sets of covariates are the only ones that significantly help explain all outcomes despite the fact that they are hard to predict, particularly

[3] This finding may be due to the fact that we cannot separate "good" interviews and visits (e.g., those from a top-ranked hiring department or those from a doctoral-granting hiring department, etc.) from other interviews and visits. Therefore, it is not empirically possible to distinguish whether the reduction in number of interviews and visits is because the candidates are receiving less, but more exclusive, interviews and visits, or simply obtaining less of them.

campus visits offered (Close et al. 2011). Placement communities are most important for interviews and campus visits obtained, but departmental characteristics play the pivotal role in determining salary, followed by placement and candidate characteristics.

7. Discussion

In this article, we propose that human brand managers may substantially influence job market outcomes, and verify this proposition in the context of the entry-level marketing job market. Specifically, we find that candidates' salary, campus visits offered, and AMA interviews obtained are all strongly influenced by advisors' membership in coauthorship and placement communities. These findings generate important implications.

7.1. Implications for Human Branding and Related Theories

Whereas previous studies considered human brand managers as "human co-brands" (e.g. Close et al. 2011), we recognize in our conceptualization that human brand managers may influence job market success for their managed human brands via their own social networks. More generally, our results can enrich other theoretical perspectives, such as the resource-based view of the firm and social capital, as we reveal that human brand managers/advisors and their networks are a resource to the job candidate. This specific resource is added social capital – the candidate can enjoy benefits from being connected to a human brand manager who is connected to influential others. This enhanced social capital, in turn, grants signaling advantages to human brands with well-connected human brand managers.

We believe a particular area where our results may illuminate further research is in the domain of signaling theory (Spence 2002). A human brand's value is determined by their human brand cues, which signal their quality. Information about candidate quality is generally asymmetric. Importantly, human brand managers may leverage their networks to send quality signals as we show. Consequently, the human brand manager and its managed brand both engage in marketing within this market, signaling quality for the human brand. Interestingly, the human brand may not be most effective to this end. Questions about coordination between the human brand manager and the human brand, and which equilibrium strategies arise in this setting, invite further theoretical and empirical investigation.

7.2. Implications for Studies on Job Markets and Social Networks

Job market studies generally do not include market participants' relations with others in understanding market outcomes (e.g. Yang et al. 2009; Fernandez-Mateo and King 2011). Similarly, although social network studies, by definition, include social connections, these often focus on how social connections benefit the connected member (e.g. Gonzalez et al. 2014). Our empirical results highlight that including the human brand managers' social networks in empirical specifications that attempt to determine job market success factors for the managed human brand (that is, for an agent that is not well-connected on his own) may be critical; ignoring these may yield biased estimates and, hence, incorrect conclusions. For example, in our salary equation, more than half of the variables with the largest effect on the market outcome (11 out of 21) are community variables.

A potential challenge to the generalizability of the above statement is that, in our setting, human brand managers market their human brands to each other, unlike in other settings. However, in our data, more than 60% of the hiring departments do not have a Ph.D. program, which implies that most of the placements do not involve relationships between two human brand managers. Separately, we acknowledge that, in other settings, a human brand managers' networks may be less visible or important. Nonetheless, given the strength of the effect of human brand managers' social networks on job market outcomes in our study, such effects are likely to persist in other contexts, albeit to a lesser degree. This only strengthens our call about the need to measure the influence of these connections on job market success.

7.3. Implications for the Marketing Market

Based on our placement and coauthorship data, our results reveal important insights that doctoral students, doctoral candidates, and advisors may use to fine-tune their job market strategies. The role of advisors in shaping market outcomes cannot be understated. We find that these memberships are most critical in the job market: advisors' community memberships are key drivers for job market success across the job market process, and placement communities are more important than coauthorship communities when it comes to determining salaries (a difference of $7,917, on average). This result is new in this stream in the literature, and its main insight is that advisor selection is a critical decision for job candidates not only to participate in the market with their advisor as a strong signal, but to leverage on their advisor's connections to increase their job market success. Our results also point out that an advisor with strong research productivity may not necessarily be an ideal choice, but rather an advisor who belongs to an influential community. While advisor productivity increased salary by $557.70, an advisor's membership in the most influential community increased salary by $23, 419.03. Overall, we advise doctoral students and candidates to choose their advisors carefully; they should consider not only their potential advisors' publication record but also *the company their potential advisors keep*.

We also find that prior success in the market predicts future success, in particular for salary. Positive market results carry over from stage to stage. Thus, it is important that job candidates strive to do well in each stage of the job market process. Furthermore, anecdote suggests that some job candidates refuse to send additional application letters to remain exclusive or to focus on only a small set of departments. Our findings counter this claim, as we find that application letters positively impact number of interviews. Furthermore, our results show a baseline interview-visit ratio of 5:1, and the expected number of interviews can rise or fall with respect to this baseline as a result of other candidate and advisor characteristics. Thus, our results can help candidates and departments obtain a rough estimate of final market success as a function of the earlier market stages and plan accordingly.

Previous research stresses the role of departments' top-ranked status as critical for the job market (Zamudio et al. 2013). Our results confirm this observation partially, as it only holds for the salary and visit stages. Because the top-ranked effect is not present at the earliest job market stage, job candidates from top degree-granting departments should mind the rest of their portfolio and not rely too highly on this cue in the first stage. Conversely, advisors' coauthorship influence is only helpful at the earliest stage but not further down the road, and thus this should be leveraged upon early.

Job candidates' characteristics influence job market outcomes in a number of ways. Modelers derive a positive benefit from their field of research specialization throughout the job market, perhaps due to their scarcity. Having a proposal defended with data at the interview stage is not a necessity, but there is no penalty from arriving at the market with a relatively underdeveloped dissertation proposal. Indeed, our results show that candidates can only benefit from strong dissertation proposals, but not the converse. This may be because hiring departments in the job market only cursorily examine dissertation topics and job market papers, perhaps without fully revising the candidate's dissertation proposal.

As to research productivity, although any publication type is conducive to job candidates' higher salary, this is not true for earlier stages of the job market. We find that A-level articles past first review are critical in the interview stage. This result may suggest that hiring departments are most interested in A-level publications close to publication, but not yet published, such that these "hits" may land after the candidate is hired and benefit the rankings of the hiring department. This merits close attention, for if candidates publish an A-level article too early, their published affiliation may be with their degree-granting department instead of their hiring department, which does not improve the latter's rankings. Conversely, an A-level publication conveys a substantial salary increase. Consequently, job candidates and their advisors should carefully plan their submission strategy to address this "tension" between having an A-level article under review to garner more initial interest and, potentially, use it as a "hit" for tenure, or having a published A-level article to bolster salary.

7.3. Limitations and Future Research

Obtaining qualitative information such as cover letter characteristics or hiring departments' rating of "soft" skills such as English or public speaking is currently missing in the literature, and would be desirable, yet these are difficult to gather retrospectively. Furthermore, no data currently exists on "closed-door" or private, undocumented exchanges pertaining to each candidate that may further add to our understanding of job market success.

In terms of data analysis, there is no way to distinguish between "good" and "bad" interviews because of data limitations. Distinguishing among these in such a way may yield additional insights. Furthermore, our data allows us to conclude that advisors' membership in coauthorship and placement social networks influences job market success; however, we are not able to disentangle whether this influence occurred due to advisors' active market participation because such effort is unobservable. Finally, a limitation that permeates most studies into job markets, including ours, is that we do not have data on candidates who participated in the market and did not find a job.

Ultimately, candidates should strive to work diligently to prepare themselves for the market. However, the insight from this article highlights the presence of other strategic elements critical for the marketing market previously unaddressed, such as the role of advisors' relations with others and the tension between publishing now or later. The former is, perhaps, our biggest contribution – to put numbers behind the assumption that our advisors matter.

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FIGURE 1
Advisor Placement Communities in Marketing Academia (2003-2007)

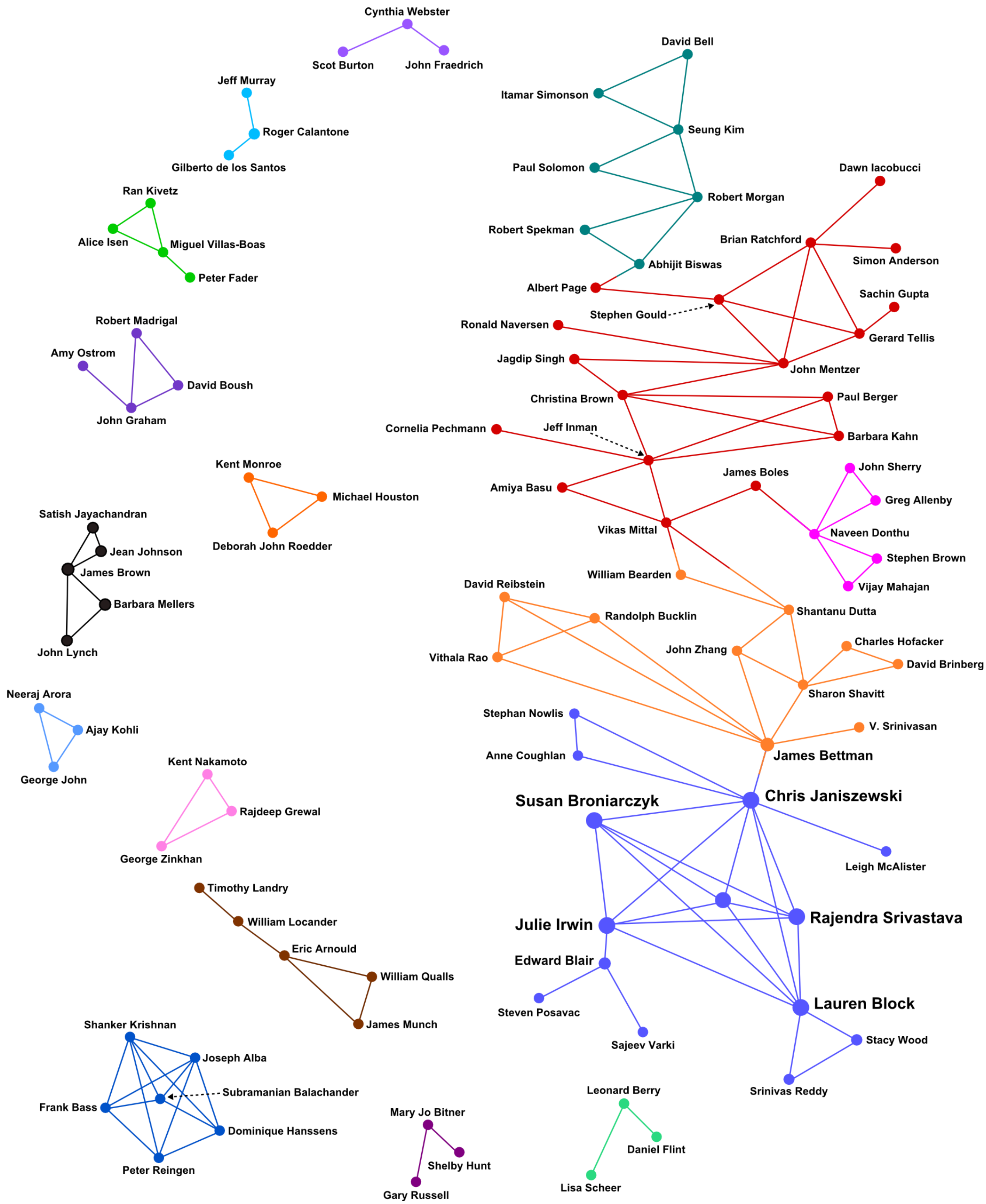

TABLE 1
Marketing Scholar Characteristics in Placement Dataset (2003-2007)

Variable	Mean	Std. Dev.	Minimum	Maximum
Job market metrics				
Application letters sent	63.93	36.65	0	200
Interviews obtained	19.12	9.30	0	40
Campus visits obtained	6.61	3.97	0	25
Campus visits accepted	5.02	3.18	0	18
Job offers obtained	2.76	1.70	1	11
9-month adjusted salary	121,310.50	25,113.72	65,405	177,000
Degree-granting department's characteristics				
Public department	0.80	0.40	0	1
Top Ranked department	0.41	0.49	0	1
Departmental avg. research productivity in A-level journals	13.47	14.72	0	64.44
Cost of Living (COLI) in degree-granting department's city	105.17	30.28	62.59	239.2
Job candidate human brand cues				
Field of research – Consumer Behavior (CB)	0.52	0.50	0	1
Field of research – Modeler	0.18	0.38	0	1
Field of research – Strategy	0.31	0.46	0	1
Proposal defended, no data	0.24	0.43	0	1
Proposal defended, with data	0.48	0.50	0	1
Conference proceedings published	4.30	3.13	0	21
A-level journal submissions	0.50	0.76	0	5
A-level journal submissions past first review	0.30	0.64	0	5
A-level journal publications	0.20	0.55	0	4
B-level journal submissions	0.49	0.92	0	6
B-level journal submissions past first review	0.29	0.62	0	3
B-level journal publications	0.73	1.18	0	6
Sheth Consortium attendance	0.78	0.59	0	2
Advisor human brand cues				
Num. of past dissertations advised	6.48	5.22	0	26
Number of top publications	9.97	8.48	0	45

N=324 placements

TABLE 2
Aggregate Advisor Characteristics in 15 Most Represented Coauthorship Communities, 2003-2007

ID	Advisors in data associated with community (all, in alphabetical order by last name)	Members in data	Average Influence	Average Cum. Num. of papers	Average Research Inactivity	Average % Top M Journal Coauthorships	Average % Other-M Journal Coauthorships	Average % Non-M Journal Coauthorships	%CB	%MOD
C1	Joseph Alba, Amiya Basu, David Bell, Paul Berger, James Bettman, C. Bhattacharya, Lauren Block, Eric Bradlow, Susan Broniarczyk, Bart Bronnenberg, Christina Brown, Randolph Bucklin, Joel Cohen, Anne Coughlan, Ravi Dhar, Peter Fader, Valerie Folkes, Srinath Gopalakrishna, Rajdeep Grewal, Stephen Hoch, Jeffrey Inman, Alice Isen, Chris Janiszewski, Joseph Kissan, Barbara Kahn, Ran Kivetz, Aradhna Krishna, Lakshman Krishnamurthi, Nanda Kumar, Gary Lilien, Leigh McAlister, Barbara Mellers, Geeta Menon, James Munch, Kent Nakamoto, Chakravarti Narasimhan, Stephan Nowlis, Cornelia Pechmann, Steven Posavac, William Qualls, Srinivas Reddy, Gary Russell, Venkatesh Shankar, Baba Shiv, Itamar Simonson, Venkat Srinivasan, Rajendra Srivastava, John Zhang	48 (20.78%)	0.21	16.42	1.02	0.85	0.06	0.08	0.48	0.38
C2	Michael Ahearne, Subramanian Balachander, Frank Bass, William Black, Pradeep Chintagunta, Wayne DeSarbo, Sachin Gupta, Dominique Hanssens, James Hess, Wagner Kamakura, Richard Lancioni, Thomas Madden, Vijay Mahajan, Naresh Malhotra, Vikas Mittal, Brian Ratchford, David Reibstein, William Ross, Lisa Scheer, K. Sudhir, Debabrata Talukdar, Miguel Villas-Boas, Dick Wittink	23 (9.96%)	0.25	24.04	0.65	0.81	0.14	0.05	0.17	0.65
C3	Mary Jo Bitner, Michael Brady, Stephen Brown, Tamer Cavusgil, Joseph Cronin, Kenneth Evans, George Franke, Gary Frankwick, Bruce Huhmann, Michael Hyman, Dawn Iacobucci, Timothy Landry, Michael Minor, Charles Noble, Amy Ostrom, Peter Reingen, James Ward	17 (7.36%)	0.04	12.06	1.35	0.42	0.41	0.17	0.53	0
C4	William Bearden, Abhijit Biswas, Paul Boughton, Robert Bunkrant, Scot Burton, Peter Dickson, Michael Hartline, Bruce Money, Marsha Richins, Randall Rose, Daniel Sherrell, Terence Shimp, Eric Spangenberg, Brian Till, Kevin Voss, Stacy Wood, Richard Yalch	17 (7.36%)	0.07	17.06	2.41	0.58	0.31	0.11	0.76	0
C5	Leonard Berry, Sundar Bharadwaj, Tom Brown, Gordon Bruner, Paul Busch, Alan Bush, Victoria Bush, Terry Clark, John Fraedrich, Satish Jayachandran, William Locander, John Mowen, Hugh O'Neill, David Ortinau, Paul Solomon, Rajan Varadarajan	16 (6.93%)	0.06	15.63	1.44	0.48	0.30	0.21	0.31	0

Community detection: N (pairs) = 54,066; N (authors) = 30,897. *Advisors in placement dataset*: N=231

TABLE 2 (continued)
Aggregate Advisor Characteristics in 15 Most Represented Coauthorship Communities, 2003-2007

ID	Advisors associated with community (all, in Eigenvector centrality order)	Members in data	Average Influence	Average Cum. Num. of papers	Average Research Inactivity	Average % Top M Journal Coauthorships	Average % Other-M Journal Coauthorships	Average % Non-M Journal Coauthorships	CB%	MOD%
C6	Chris Allen, James Boles, Thomas Brashear, James Gentry, Ronald Hasty, Shelby Hunt, Eli Jones, Debra Laverie, Karen Machleit, Robert Morgan, Jeff Murray, Julie Ozanne, Robert Spekman	13 (5.63%)	0.05	12.46	2.15	0.45	0.40	0.15	0.46	0
C7	Terry Childers, Ruby Dholakia, Shantanu Dutta, Michael Houston, George John, Ajay Kohli, Shanker Krishnan, Deborah MacInnis, C. Whan Park, Surendra Singh, Gerard Tellis	11 (4.76%)	0.06	19.91	0.64	0.71	0.19	0.10	0.55	0.27
C8	Eric Arnould, David Brinberg, Bobby Calder, Stephen Gould, Zeynep Gurhan-Canli, John Lynch, Durairaj Maheswaran, Ann McGill, Joan Meyers-Levy, George Milne, J. Craig Thompson	11 (4.76%)	0.09	13.64	0.55	0.68	0.25	0.07	0.73	0
C9	Sharon Beatty, John Deighton, Lynn Kahle, Nicole Ponder, Kristy Reynolds, Roland Rust, Steven Shugan, Sajeev Varki	8 (3.46%)	0.16	19.13	1.63	0.55	0.23	0.22	0.63	0.13
C10	Roger Calantone, Patricia Daugherty, Michael Hu, Matthew Myers, Stephanie Noble, Eric Shaw, Jinhong Xie	7 (3.03%)	0.08	18.43	1	0.30	0.41	0.29	0.14	0.29
C11	Robert Dwyer, Jule Gassenheimer, Robert Madrigal, Ronald Michaels, Barton Weitz	5 (2.16%)	0.07	13.6	4	0.72	0.22	0.06	0.2	0
C12	Richard Bagozzi, Dipankar Chakravarti, Julie Irwin, Shaun McQuitty, Joydeep Srivastava	5 (2.16%)	0.23	17	1.4	0.77	0.13	0.10	0.8	0.2
C13	David Boush, Theodore Farris, John Ford, John Ozment, Audhesh Paswan	5 (2.16%)	0.02	9.8	2.6	0.14	0.65	0.21	0.4	0
C14	Edward Blair, Betsy Gelb, Charlotte Mason, Cynthia Webster, George Zinkhan	5 (2.16%)	0.12	26.6	1.4	0.31	0.48	0.21	0.8	0
C15	Michael Brusco, Brian Engelland, Leisa Flynn, Ronald Goldsmith, Charles Hofacker	5 (2.16%)	0.01	7.6	4.2	0.51	0.21	0.27	0.8	0.2

Community detection: N (pairs) = 54,066; N (authors) = 30,897. *Advisors in placement dataset*: N=231

TABLE 3
Aggregate Advisor Characteristics in 10 Most Active Placement Communities, 2003-2007

ID	Members (in alphabetical order, by last name)	# placements (% of total)	CB%	MOD%	Average top pubs/advisor	Average dissertations chaired/advisor	Avg. Candidate Salary ($)	Avg. Candidate Visits	Avg. Candidate Interviews	Hiring departments with most placements
P1	Amiya Basu, Paul Berger, James Boles, Christina Brown, Stephen Gould, Sachin Gupta, Dawn Iacobucci, Jeff Inman, Barbara Kahn, John Mentzer, Vikas Mittal, Ronald Naversen, Albert Page, Cornelia Pechmann, Brian Ratchford, Jagdip Singh, Gerard Tellis	32 (9.88%)	43.75	31.25	43.75	6.88	129,578.72	6.03	20.31	*43.75% of placements in:* Boston College (4) Lehigh (4) Mississippi (3) Oregon (3)
P2	Ed Blair, Lauren Block, Susan Broniarczyk, Anne Coughlan, Julie Irwin, Chris Janiszewski, Leigh McAlister, Stephan Nowlis, Steven Posavac, Srinivas Reddy, Rajendra Srivastava, Rajan Varadarajan, Sajeev Varki, Stacy Wood	23 (7.10%)	71.43	14.29	71.43	4.43	130,053.34	6.69	20.48	*52.17% of placements in:* South Carolina (6) Washington (3) Loyola Maryland (3)
P3	William Bearden, James Bettman, David Brinberg, Randolph Bucklin, Shantanu Dutta, Charles Hofacker, Vithala Rao, David Reibstein, Sharon Shavitt, V. Srinivasan, John Zhang	18 (5.56%)	30	60	30	4.20	140,296.94	8.5	25.44	*61.11% of placements in:* Minnesota (4) Maryland (4) Kansas State (3)
P4	David Bell, Abhijit Biswas, Seung Kim, Robert Morgan, Itamar Simonson, Paul Solomon, Robert Spekman	15 (4.63%)	42.86	14.29	42.86	7.86	115,311.53	6.4	21.8	*60% of placements in:* James Madison (3) CUNY-Baruch (3) Northern Illinois (3)
P5	Greg Allenby, Stephen Brown, Naveen Donthu, Vijay Mahajan, John Sherry	10 (3.09%)	20	40	20	11.20	128,341.2	5.8	16.4	*60% of placements in:* Notre Dame (3) Drexel (3)
P6	Eric Arnould, Timothy Landry, William Locander, James Munch, William Qualls	8 (2.47%)	80	0	80	5	107,954.62	4.88	14.25	*37.5% of placements in:* Cal. State Long Beach (3)
P7	James Brown, Satish Jayachandran, Jean Johnson, John Lynch, Barbara Mellers	8 (2.47%)	40	0	40	6	112,276.23	6.25	21.25	*75% of placements in:* Saint Thomas (3) Illinois State (3)
P8	Joseph Alba, Subramanian Balachander, Frank Bass, Dominique Hanssens, Shanker Krishnan, Peter Reingen	7 (2.16%)	33.33	50	33.33	8.17	143,421.85	7.29	22.14	*85.71% of placements in:* Central Florida (6)
P9	David Boush, John Graham, Robert Madrigal, Amy Ostrom	7 (2.16%)	75	0	75	3.75	111,961.42	6.43	13.14	*42.85% of placements in:* San Diego (3)
P10	Peter Fader, Alice Isen, Ran Kivetz, Miguel Villas-Boas	6 (1.85%)	50	50	50	4	162,041.57	12.33	23.33	*50% of placements in:* University of Chicago (3)

N (advisors) =231; N (candidates) = 324.

TABLE 4
Effects of Candidate, Advisor and Market Characteristics on Job Market Outcomes

Covariate type	Covariate	9-month adj. salary regression	Visits offered regression	Interviews obtained regression
Job market outcomes	Application letters	18.50	-0.002	0.13***
	AMA interviews	23.66	0.24***	- - -
	Campus visits accepted	54.53	- - -	- - -
	Offers obtained	1,785.99***	- - -	- - -
Degree-granting department's (DGD) characteristics	Public DGD	-4,385.29	-0.82	-0.45
	Top-Ranked DGD	10,239.61***	1.43***	-0.42
	Departmental top pub. average	138.44	-0.05***	0.00
	COLI in DGD's city	12.73	0.01	0.02
	DGD & HD in same dept. comm.	-1,383.11	0.05	0.35
Candidate's field of research	CB	725.27	0.60	0.75
	Modeler	8,626.40***	1.07**	2.98***
Candidate's dissertation status	Defended, no data	3,615.97	-0.56	2.53***
	Defended with data	5,140.75***	-0.01	1.75
Candidate's research productivity and honors	Proceedings publication	639.79***	0.13***	0.03
	A article – Submitted	790.10	-0.02	0.02
	A article – Past first review	2,294.97	-0.03	2.77***
	A article – Published	4,834.99***	0.93***	-0.12
	B article – Submitted	-602.79	0.11	-0.16
	B article – Past first review	-297.93	-0.21	0.38
	B article – Published	1,678.64***	-0.17	0.06
	Sheth Consortium attendance	4,081.24***	0.06	-0.80
Advisor's characteristics	Avg. num. of diss. chaired	-394.17***	-0.02	0.06
	Number of top publications	577.70***	-0.02	-0.10
	Influence in Marketing scholarship (Eigenvector centrality of coauthorship)	-4,420.19	1.85	13.74***

DGD: Degree-granting department. HD: Hiring department. COLI: Cost of living. N (advisors) =231; N (candidates) = 324. Significant estimates marked with *** (99%), ** (95%) or * (90%). Breusch-Pagan test suggests independency of SUR equations ($\chi^2 = 0.21, p = 0.98$)

TABLE 4 (continued)
Effect of Advisor Community Membership on Job Market Outcomes

Covariate type	Covariate	Salary regression	Visits offered regression	Interviews obtained regression
Co-author ship community effects	**C1**: Joseph Alba, Amiya Basu, David Bell, Paul Berger, James Bettman et al.	11,316.76***	-0.95	-1.12
	C2: Michael Ahearne, Subramanian Balachander, Frank Bass, William Black, Pradeep Chintagunta et al.	3,802.21	-0.13	0.65
	C3: Mary Jo Bitner, Michael Brady, Stephen Brown, Tamer Cavusgil, Joseph Cronin et al.	8,354.59***	-0.91	1.18
	C4: William Bearden, Abhijit Biswas, Paul Boughton, Robert Bunkrant, Scot Burton et al.	3,216.25	0.33	0.45
	C5: Leonard Berry, Sundar Bharadwaj, Tom Brown, Gordon Bruner, Paul Busch et al.	8,082.54**	1.82***	0.53
	C6: Chris Allen, James Boles, Thomas Brashear, James Gentry, Ronald Hasty et al.	5,320.75	0.83	-0.14
	C7: Terry Childers, Ruby Dholakia, Shantanu Dutta, Michael Houston, George John et al.	2,997.11	-1.06	0.08
	C9: Sharon Beatty, John Deighton, Lynn Kahle, Nicole Ponder, Kristy Reynolds et al.	4,359.57	-0.04	0.58
	C10: Roger Calantone, Patricia Daugherty, Michael Hu, Matthew Myers, Stephanie Noble et al.	5,766.01	-0.52	0.86
	C11: Robert Dwyer, Jule Gassenheimer, Robert Madrigal, Ronald Michaels & Barton Weitz	11,808.95**	1.19	-1.33
	C12: Richard Bagozzi, Dipankar Chakravarti, Julie Irwin, Shaun McQuitty & Joydeep Srivastava	15,149.58***	-0.60	-2.20
	C13: David Boush, Theodore Farris, John Ford, John Ozment & Audhesh Paswan	7,360.87	0.01	-3.36
	C14: Edward Blair, Betsy Gelb, Charlotte Mason, Cynthia Webster & George Zinkhan	7,995.07	-0.21	-1.75
	C15: Michael Brusco, Brian Engelland, Leisa Flynn, Ronald Goldsmith & Charles Hofacker	5,747.59	1.53	-2.31
Placement community effects	**P1**: Amiya Basu, Paul Berger, James Boles, Christina Brown, Stephen Gould et al.	10,466.99***	-1.48***	0.93
	P2: Ed Blair, Lauren Block, Susan Broniarczyk, Anne Coughlan, Julie Irwin et al.	7,642.50***	-0.32	1.64
	P3: William Bearden, James Bettman, David Brinberg, Randolph Bucklin, Shantanu Dutta et al.	10,829.40***	-0.30	6.51***
	P4: David Bell, Abhijit Biswas, Seung Kim, Robert Morgan, Itamar Simonson et al.	4,634.37	-1.44	2.52
	P5: Greg Allenby, Stephen Brown, Naveen Donthu, Vijay Mahajan and John Sherry	9,006.30**	-1.61	-3.00
	P6: Eric Arnould, Timothy Landry, William Locander, James Munch and William Qualls	893.02	-0.59	-1.85
	P7: James Brown, Satish Jayachandran, Jean Johnson, John Lynch and Barbara Mellers	5,738.52	-1.04	1.72
	P8: Joseph Alba, Subramanian Balachander, Frank Bass, Dominique Hanssens, Shanker Krishnan et al.	18,781.38***	-0.47	-2.10
	P9: David Boush, John Graham, Robert Madrigal and Amy Ostrom	-1,684.81	-0.10	-2.79
	P10: Peter Fader, Alice Isen, Ran Kivetz and Miguel Villas-Boas	23,419.03***	3.47***	2.33
	Intercept	82,128.62***	1.54	4.66
	R^2	.756	.542	.527

N (advisors) =231; N (candidates) = 324. Significant estimates marked with *** (99%), ** (95%) or * (90%)

TABLE 5
Test of R-square change for each Covariate Group (Hierarchical Regression)

Group	Salary R-square change	Visits offered R-square change	Interview R-square change
Degree-granting department characteristics	.253***	.019	.058***
Candidate characteristics	.089***	.027	.072***
Advisor's characteristics	.015***	.002	.021**
Coauthorship communities	.031***	.048***	.038***
Placement communities	.099***	.112***	.097***
R^2	.757	.542	.527

N (advisors) =231; N (candidates) = 324.
Significant estimates marked with *** (99%), ** (95%) or * (90%).