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RESEARCH ARTICLE

Which Modeling Scholars Get Promoted, and How Fast?

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Abstract The future of quantitative marketing is defined by its research output as much as by the researchers who produce it. Yet, little is known about the determinants of promotion and time to promotion among quantitative marketing scholars (or "modelers") as well as whether their early signals of attractiveness in the job market are indicative of future success. In this article, we shed light on these issues by investigating the roles that research productivity, departmental characteristics, demographics, and coauthorship play in determining promotion and time to promotion from assistant to associate professor. We find that early signals of attractiveness do not play an important role in determining modelers' promotion and time to promotion. Research productivity does, and its effect is moderated by whether modelers are employed in departments that offer Ph.D. programs. We also find that membership in various coauthorship social networks, or "communities", is a robust predictor of promotion and time to promotion.

Keywords Research productivity · Coauthorship · Academic promotion · Social networks · Quantitative marketing

1 Introduction

Extant research into the determinants of success in marketing academia has focused on how doctoral candidate and advisor characteristics influence interviews, campus visits, and salary in the marketing job market [8] and the utility generated by entry-level placements [24]. For established faculty already on the tenure-track, research has focused on the multiple determinants of salary [15] and on research productivity as a predictor of promotion [21]. Yet, despite the above advances, three important unknowns remain in the literature. First, whether signals of early job market attractiveness—such as department prestige or research productivity—predict future success (i.e., promotion) has not been studied. Second, although research productivity is known to influence promotion decisions [21], other potential determinants, such as candidates' coauthorship, demographics, and departmental characteristics, remain unknown. Third, the factors that may accelerate (or dampen) time to promotion have also not been assessed.

The future of quantitative marketing is defined by its research output as much as by the researchers who produce it. Consequently, our contribution is to provide answers to the above unknowns in the context of quantitative marketing scholars (modelers). We analyze promotions from assistant professor to associate professor using a unique dataset of 128 modelers who graduated during the 1997–2005 period. The dataset includes candidate and department characteristics variables relating to (1) research productivity, (2) prestige, (3) coauthorship, (4) demographics, and (5) hiring and degree-granting department characteristics. Our results suggest that, for modelers, the factors determining early job market attractiveness are not the same as those that determine promotion and time to promotion. Also, our results suggest that signals of early job market attractiveness are poor predictors of future promotion. Furthermore, we find that research productivity is an important determinant of promotion and time to promotion. However, the role of modelers' publication portfolios in promotion depends on the type of hiring department they are employed in—specifically, whether the department offers a Ph.D. program or not. Finally, we find that modelers'

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membership in important coauthorship social networks is a robust predictor of promotion and time to promotion.

The remainder of the paper is organized as follows. In Section 2, we discuss modelers' patterns of development. In Section 3, we investigate the presence of coauthorship networks in marketing academia and determine modelers' membership in these networks. Section 4 presents the results of our promotion and time to promotion analyses. Section 5 discusses and concludes with directions for future research.

2 Patterns of Development Among Tenure-Track Modelers

Marketing scholars may develop in various ways throughout their academic careers. For example, their patterns of research productivity may be different, such that some scholars exhibit a consistently high research output throughout their career whereas others decline over time, among other patterns [18]. To assess the patterns of development among modelers, we use a sample of 128 modeling scholars, which we call the *promotion dataset*. This dataset includes modelers that started their first tenure-track academic job[1] during the 1997–2005 period. This period was chosen to allow sufficient time to potentially observe the scholars of the last year recorded (2005) to be promoted—8 years (2006–2014).

The promotion dataset contains the full employment and research history of each modeler up to when promotion[2] was obtained, using Web searches and personal e-mails. For modelers that did not earn promotion, their full employment and research history up to May 2014 was recorded. Table 1 displays a summary of the major characteristics of the modelers studied, and Table 2 displays correlations among these major characteristics.

Promotion Variables Our dependent variables are modelers' promotion and time to promotion—specifically, promotion from assistant professor to associate professor. Therefore, a maximum of one promotion per modeler was recorded in the promotion dataset. To examine development patterns over time, calendar years are not useful; instead, we use years elapsed after graduation as a measure of time in order to compare modelers who graduated in different years. The number of promotions per year among modelers is shown graphically in panel 1.1 of Fig. 1.

Our analysis indicates that more than half (77.34 %) of modelers were promoted, with the earliest time to promotion being 3 years. Indeed, observing a time to promotion below the usual contractually stipulated 6 years is rare, with only 21 modelers (16.40 %) being promoted within this short time frame. The most common is promotion within 6 to 8 years (46.88 % of modelers) with the rest of the observed promotions occurring afterwards. No promotions were observed after the 11th year.

Interestingly, less than half (44.53 %) of the modelers in the promotion dataset obtained promotion in their first place of employment. This means that modelers, more likely than not, will have to move to a second place of employment to achieve promotion. Importantly, these moves have implications for modelers' future career prospects because as modelers move from department to department, the profile of the hiring department in which they will settle in changes. A visual summary of this changing profile is shown in Fig. 1, panel 1.2.

In the panel, we denote modelers' first place of employment as their "first position." Thus, the first position depicted describes the typical department a modeler is hired at upon graduation as well as the cumulative percentage of modelers that were promoted in their first position. These first positions are predominantly in Ph.D. granting departments (85.94 % of first positions), which is considered a successful job market outcome [24], and also within the USA (89.84 %). Slightly more than half of the first positions observed (60.94 %) are in departments classified as "top 30," that is, the most prestigious departments in marketing academia as measured by research and MBA rankings [24]. This is reassuring for the future of quantitative marketing, as positions taken in departments of such prestige, regardless of whether scholars achieve promotion there or not, have been shown to bolster scholars' research productivity and others' perception of the quality and importance of their research portfolio [1].

As modelers move to second and third employment positions, we observe a slight increase in the likelihood that modelers are promoted, of 7 and 8 %, respectively, with no promotions being observed after the third move. However, the profile of the hiring department that modelers may work in after such moves changes considerably. Specifically, we find a decline in the likelihood of being hired by a top 30 department by −8 and −12 %, respectively. The chance to work at a Ph.D. granting department (−15 % and −30 %) as well as a department in the USA (−6 and−24 %) also diminishes considerably as the modeler moves from the second to the third employment position.

[1] In order to ensure adequate comparability among the modelers in our promotion dataset, we follow extant literature [24] and only include modelers whose first job was a tenure-track job in the analysis. Therefore, modelers who started as visiting scholars, non-tenure track faculty, or postdocs were not included. Similarly, modelers whose doctoral degree is not in marketing were not included as well.

[2] Promotion and tenure decisions are separate in some departments: a scholar can be promoted, initially, but without indefinite tenure. Because we do not directly observe these separate decisions, we focus on promotion decisions. However, in our sample of 128 modelers, only one modeler was observed to disclose separate promotion and tenure decisions.

Table 1 Descriptive statistics, modeler sample 1997–2005

	Modelers not promoted	Modelers promoted			
Variable	Average	Average	Standard deviation	Minimum	Maximum
Promotion variables					
Modelers promoted	29 (22.66 %)	99 (77.34 %)	–	–	–
Years to promotion[a]	11.21	6.79	1.96	3	11
Number of places of employment	1.86	1.53	0.69	1	4
Research productivity					
Number of publications upon graduation	0.45	0.89	1.18	0	7
In tier 1 marketing journals	0.07	0.29	0.59	0	3
In tier 2 marketing journals	0.07	0.19	0.49	0	2
In tier 3 marketing journals	0.10	0.20	0.71	0	6
In other marketing journals	0.21	0.19	0.57	0	4
In non-marketing top journals	0.00	0.01	0.10	0	1
Number of publications after graduation	4.41	6.09	3.16	1	21
In tier 1 marketing journals	1.90	3.45	2.18	0	8
In tier 2 marketing journals	0.79	1.16	1.18	0	6
In tier 3 marketing journals	0.83	0.54	1.03	0	6
In other marketing journals	0.79	0.740	1.04	0	5
In non-marketing top journals	0.10	0.20	0.52	0	2
Coauthorship variables					
Average no. of authors in publications	3.02	3.11	1.00	1.33	7.40
Membership in coauthorship communities	13 (44.83 %)	72 (72.72 %)			
In community 1	1 (3.45 %)	6 (6.06 %)	–	–	–
In community 2	1 (3.45 %)	10 (10.10 %)	–	–	–
In community 3	6 (20.69 %)	21 (21.21 %)	–	–	–
In community 4	5 (17.24 %)	35 (35.35 %)	–	–	–
Modeling scholars' characteristics					
Modelers from top 30 degree-granting departments	26 (89.66 %)	89 (89.90 %)	–	–	–
Male modelers	18 (62.07 %)	80 (80.80 %)	–	–	–
Modelers from USA/Canada	7 (24.14 %)	15 (15.15 %)	–	–	–

N=128. Sample percentages, instead of averages, shown if variable is discrete. All other percentages and calculations are with respect to full sample. Research productivity note: Total number of publications 832. QME was founded in 2000. The rest of the journals were founded before 1997. USA/Canada note: We consider a modeler from USA/Canada if he or she obtained a baccalaureate degree in the USA [20]

[a] Percentages and calculations are with respect to modelers who obtained promotion.

Research Productivity Research productivity has been previously shown to predict promotion and future career success [21, 2]. As such, we incorporated this critical variable in our analysis by collecting the publications of each modeler in the promotion dataset, along with the number of authors in each, until the year the modeler was promoted. We subdivided the journals in which modelers published in into four tiers [15, 24]. Tier 1 includes the *Journal of Consumer Research*, *Journal of Marketing*, *Journal of Marketing Research*, and *Marketing Science*. We add *Management Science* to this list due to its stature in the modeling community [24]. Tier 2 includes the *International Journal of Research in Marketing*, *Journal of Consumer Psychology*, *Journal of Retailing*, *Journal of the Academy of Marketing Science*, and *Marketing Letters*. *Quantitative Marketing and Economics* was also added to this tier due to its stature among the modeling community as well. Tier 3 includes all other marketing journals not included in this list. Tier 4 includes all journals outside of marketing. This last tier was further subdivided into two subcategories—top tier 4 and other tier 4—as several journals outside of marketing are highly ranked and thus could influence promotion outcomes[3] [15]. Until promotion, modelers published 832 journal articles, 428 (51.44 %) in tier 1 journals, 159

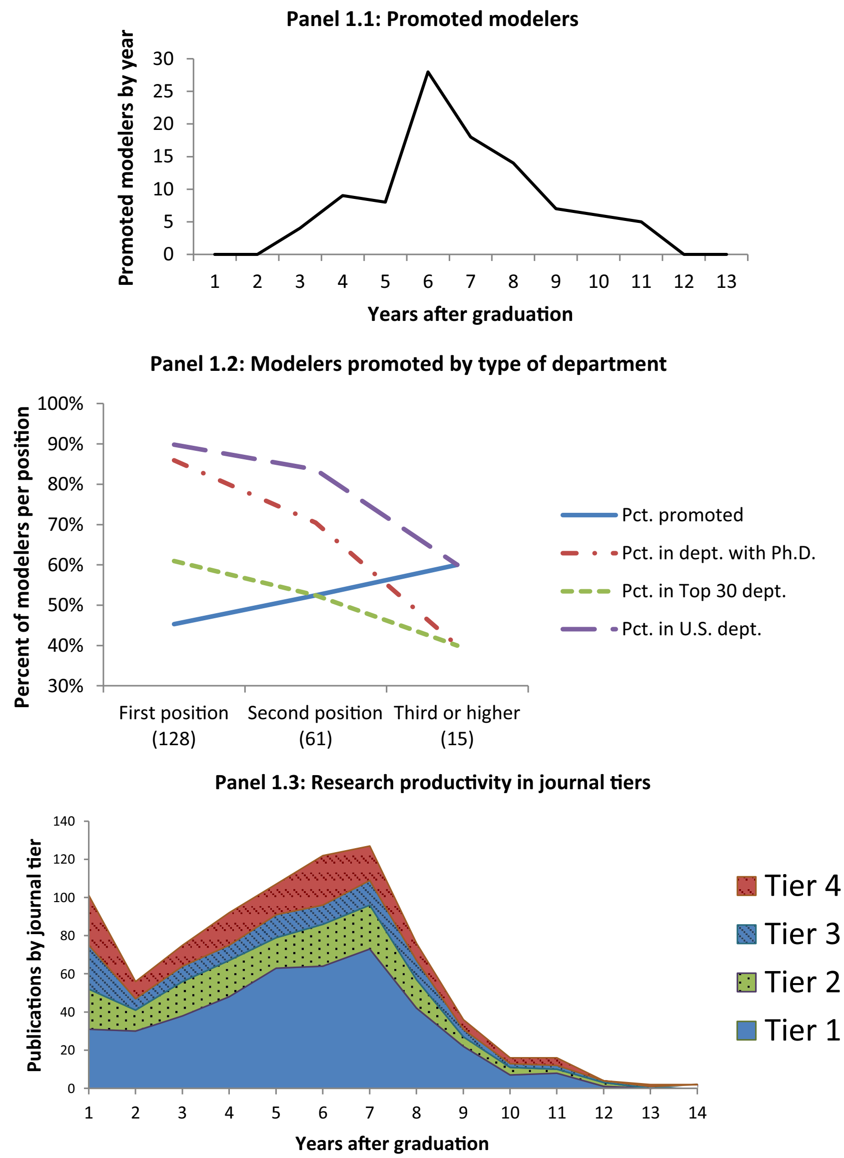
[3] A classification of journals outside marketing into a top category and a non-top category has been proposed previously [15]. We follow this previous approach in constructing our top tier 4 and tier 4 subcategories, but we do not include the "Practitioner Journals" category (*Harvard Business Review, Interfaces, Sloan Management Review*).

Table 2 Correlations table. These comprise data from modelers who graduated during 1997–2005

Vars.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	1.00																			
2	−0.48	1.00																		
3	0.02	0.09	1.00																	
4	−0.05	−0.02	0.33	1.00																
5	0.09	−0.13	0.17	0.28	1.00															
6	0.09	−0.17	0.10	0.20	0.29	1.00														
7	0.03	−0.15	−0.01	0.13	0.41	−0.01	1.00													
8	−0.11	0.01	0.03	0.13	0.33	0.20	0.26	1.00												
9	0.48	−0.32	0.09	−0.03	0.30	0.05	0.23	0.09	1.00											
10	0.26	−0.22	−0.13	−0.16	0.14	0.09	−0.03	0.04	0.22	1.00										
11	0.06	−0.09	−0.04	−0.20	−0.11	0.02	−0.17	0.11	−0.01	−0.05	1.00									
12	0.17	−0.02	−0.08	−0.03	−0.03	0.05	−0.10	0.07	0.08	0.15	0.15	1.00								
13	0.20	−0.15	−0.16	−0.19	−0.03	−0.03	−0.10	−0.02	0.09	0.10	0.20	0.07	1.00							
14	0.41	−0.28	−0.01	−0.09	0.19	0.11	0.02	0.11	0.59	0.59	0.28	0.41	0.22	1.00						
15	0.12	−0.10	0.03	0.05	0.04	0.04	−0.03	−0.04	0.09	0.02	−0.04	−0.02	0.13	0.00	1.00					
16	−0.12	0.25	0.15	0.11	0.04	0.14	−0.12	0.13	−0.14	−0.11	0.10	−0.06	−0.03	−0.08	−0.18	1.00				
17	0.13	−0.21	0.13	0.13	0.11	0.05	0.12	−0.02	0.06	−0.00	−0.03	−0.04	−0.04	−0.00	−0.01	0.04	1.00			
18	−0.03	0.15	0.10	−0.06	−0.08	0.03	−0.14	0.11	−0.05	0.02	−0.10	0.00	−0.05	−0.01	0.03	0.25	−0.17	1.00		
19	−0.02	0.01	−0.12	0.02	0.11	−0.04	−0.01	0.01	0.01	0.14	0.01	−0.05	0.07	0.08	0.17	−0.02	−0.22	−0.09	1.00	
20	0.00	0.03	0.11	0.05	0.06	0.02	0.12	0.07	0.10	0.06	−0.02	−0.02	−0.10	0.06	−0.03	−0.05	−0.33	−0.14	−0.18	1.00

The following are the variables included in the correlations table. 1 modeler was promoted (dependent variable), 2 years to tenure, 3 top 30 degree-granting department, 4 private degree-granting department, 5 top 30 hiring department, 6 private hiring department, 7 hiring department has Ph.D. program, 8 hiring department in the USA, 9 publications tier 1, 10 publications tier 2, 11 publications tier 3, 12 other publications tier 4, 13 top publications tier 4, 14 avg. no. of coauthors, 15 male modeler, 16 modeler from the USA, 17 community 1, 18 community 2, 19 community 3, 20 community 4

Fig. 1 Modelers' patterns of development



(19.11 %) in tier 2 journals, 30 (3.60 %) in top tier 4 journals, and the rest in other tiers.

Research productivity changes over time, as modeling scholars approach promotion at their first place of employment and then, if not promoted, move elsewhere. Figure 1, panel 1.3, outlines the number of publications in different journals over time. The first year after graduation shows a peak because it includes publications before graduation as well. The publication count is always dominated by tier 1 publications, regardless of the year after graduation, except after the 12th year.

3 Modelers' Coauthorship Networks

Another factor that could influence promotion is coauthorship. Although this factor and its impact on academic career success has not been as widely studied as research productivity, previous research has investigated it in the context of the entry-level market, where the effect of the number of coauthors a job candidate has on hiring decisions was found to be marginal [24]. However, the *number* of coauthors a modeler has reflects only his or her active collaboration with more authors. For instance, in the promotion sample, modelers, on average, feature 3.09 authors in their publications.

Evidence exists, however, suggesting that academics' *association* with others may benefit them in the long run, specifically, when academics associate with prestigious degree-granting departments and the faculty therein [2]. For this reason, we chose to explore whether modelers, by virtue of being associated with *specific*, enduring groups of coauthors, may enjoy a higher chance of promotion or a faster time to promotion. The first step in this analysis, thus, is to determine the coauthorship networks that modelers are members of.

To detect and characterize these networks, we use a coauthorship information dataset made available by Goldenberg and colleagues [10], which we call the *coauthorship dataset*. The coauthorship dataset contains more than 30,000 scholars that coauthored in the leading journals during the 1973–2007 period. The coauthorship dataset was used to capture information about the specific scholars that modelers in the promotion dataset collaborate with. In particular, we applied a social network community detection algorithm, known as the Louvain algorithm [3], to the coauthorship dataset. The algorithm allowed us to endogenously discover groups or "communities" of scholars that consistently publish together in marketing academia. Once these communities were found, they were appended to the promotion dataset: if a modeler in the promotion dataset was associated to one of the major communities found in the coauthorship dataset, this was recorded in the promotion dataset for use in subsequent analysis.

3.1 Detecting Unobserved Communities in the Coauthorship Dataset

To detect communities within large networks, the community detection algorithm employed in this article relies on a clustering metric known as modularity [16]. Suppose that there are a finite number of groups of actors in a social network and that each actor may belong to only one such group. For these groups of actors, a low modularity value (close to zero) indicates that the observed groups could have arisen by chance if random connections among actors occurred; conversely, a high modularity value (close to one) indicates that the groups did not arise randomly and are thus considered enduring relational structures or "communities." From the above, it can be deduced that each group in a network has a sub-modularity score that, when aggregated, forms a network-wide modularity score. In general, a network-wide modularity score above 0.3 implies a good community structure [17].

The modularity score is computed as follows. Consider a weighted, square, and undirected social network A [22]. Each actor in the social network is labeled as i. Assume that a number of communities exist in the social network and denote the community to which actor i belongs as c_i. Now, suppose a certain community c_i is eliminated, such that the ties among the actors in it were instead eliminated and randomly redistributed across the social network. It can be shown that the probability of a tie existing between any actor i and j is $\frac{k_i k_j}{2m}$, with a_{ij} being the weight of the tie between actors i and j in matrix A, m being the total number of ties between actors in the social network, and $k_i = \sum_j a_{ij}$ being the degree of actor i, that is, the sum of all ties incident to that actor [16]. Using this probability specification, the modularity score of the network can be computed as [3]:

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

where $\delta(c_i,c_j)$ is an indicator function that takes the value 1 if $i=j$ and 0 otherwise.

The community detection algorithm attempts to maximize the network-wide modularity score of a social network to arrive at a community solution for the social network. Such maximization is performed by endogenously discovering groups that contribute most to the network-wide modularity score. To this end, the algorithm operates in a series of "passes," discussed next.

Step 1 For initialization, each actor in the social network is considered to be a community, such that there are as many communities in the social network as there are actors. For each actor i, agglomerating actor i to each neighboring actor j into a community C is considered. These potential agglomerations are evaluated in terms of the network-wide modularity gain, which can be written as

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

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 $k_{i,\text{in}}$ is the sum of the weights of the ties from actor i to all other actors within proposed community C. After all agglomerations of i with j are evaluated and if any gain in modularity can be achieved, the agglomeration occurs and C becomes a new community, composed of i and j. Potential agglomerations with equal modularity gains are resolved by drawing a uniform random number.

Step 2 Once an initial set of communities has been found through the agglomerative process described above, a new social network is formed. In this new social network, each community, composed of an agglomeration of actors, becomes a new, superordinate actor or node in the network [3]. Weights among these new nodes are computed as the sum of the weight of the ties among their members such that the new social network preserves the modularity of the original [1].

Iteration and Convergence Steps 1 and 2 are known as a "pass." The algorithm iterates to form communities of higher hierarchy. The algorithm stops once no passes can be conducted because more changes can be made to the community structure—this occurs when a prespecified tolerance level is reached. A network-wide modularity maximum is then said to be attained.

The Louvain algorithm offers important advantages, such as the ability to detect communities in very large networks while remaining computationally fast as well as being able to detect communities that are small and thus hard to detect, which is known as the "resolution problem" [9]. However, the model is static, and thus, the evolution of community memberships over time is not captured. Furthermore, the model assumes that every actor in a network can only belong to one community.

3.2 Coauthorship Community Results

Using the coauthorship dataset, the community detection analysis yielded a solution with a high degree of modularity (Q=0.84) and more than 3000 communities of marketing coauthors. However, we find that most of the modelers in our promotion dataset (108 or 84.38 % of the dataset) belong to one of 17 coauthorship communities found in the coauthorship dataset. The rest of the modelers were not found to be part of any coauthorship community and are thus "unconnected." We focus our subsequent analysis on the four communities that most of the modelers in our promotion sample (85, 66.40 %) are members of. These communities have at least seven members represented in our promotion dataset.[4] Table 3 summarizes the most prominent members of these four communities as found in the coauthorship dataset; Table 4 summarizes the characteristics of the modelers in the promotion dataset who are members of those communities.

In Table 3, we show the top 30 coauthors (sorted by Eigenvector centrality) within the four communities that are associated with the modelers in our promotion sample. We rely on Eigenvector centrality as it measures the influence that actors have over the whole social network [22] and is different from simply taking the degree (i.e., counts of coauthorships) in the dataset [4]. As can be observed, there is considerable heterogeneity in Eigenvector centrality across the coauthorship communities, implying that different coauthorship communities are differently influential in the overall coauthorship structure of marketing academia.

The four communities found also vary in their average number of publications and coauthors. Importantly, marketing scholars in the four communities, as compared[5] to other scholars in the coauthorship dataset, publish more (mean difference=1.34, $t(3858.58)=13.22$, $p<0.01$), work with more coauthors (mean difference=2.20, $t(3775.68)=17.15$, $p<0.01$), and are more influential (mean Eigenvector centrality difference=0.03, $t(3584.18)=22.23$, $p<0.01$). Further, when comparing these four communities against each other, there are significant differences in research productivity ($F(3,3204.15)=11.90$, $p<0.01$), coauthorship ($F(3,2090.45)=2.91$, $p<0.01$), and influence ($F(3,2000.25)=4.67$, $p<0.01$) as well. With this in mind, one could conjecture that belonging to highly productive, influential, and collaborative coauthor communities may help modelers improve their promotion outcomes.

It must be kept in mind that, when considering our promotion sample of 128 modelers and their membership in the four communities above, we find different patterns as shown in Table 4. Whether a modeler in the promotion dataset is a member of these four communities is not associated with higher research productivity (mean difference=−0.96, $t(126)=0.1.47$, $p=0.57$) but is associated with increased average coauthorship level (mean difference=0.42, $t(115.53)=2.77$, $p<0.01$). Yet, when comparing the modelers in the promotion dataset that are associated with these four communities against each other, we find no significantly different research productivity ($F(3,20.18)=0.77$, $p=0.52$) nor coauthorship level ($F(3,81)=1.03$, $p=0.39$) patterns. Consequently, potential differences in the impact of community membership on promotion and time to promotion could not be attributable to research productivity or level of coauthorship. In our further analysis, we control for research productivity, level of coauthorship, the effect of all four coauthorship communities, and other factors. This will allow us to isolate the effect of coauthorship community membership on promotion and time to promotion.

[4] Although we found an additional community that was sufficiently represented (six members represented in the promotion dataset), neither of the members of this community had an Eigenvector centrality score superior to 0.1. Given this comparatively low level of influence, we do not focus on this additional community. However, the analyses of promotion and time to promotion are robust to including this community as well.

[5] When comparing measures related to community membership against non-community membership, independent sample t tests are used. When comparing measures among the four communities, analysis of variance is used. We use adjusted F or t statistics when the homogeneity of variances assumption (at the 10 % significance level) is not satisfied.

Table 3 Characteristics of modeling coauthorship communities, and most influential coauthors, up to 2007

Community 1		Community 2		Community 3		Community 4	
Scholar	Eigenvector centrality	Scholar	Eigenvector centrality	Scholar	Eigenvector centrality	Scholar	Eigenvector centrality
Most influential marketing scholars in coauthorship communities, Goldenberg et al. [10] sample							
Vithala Rao	0.57	Eric Greenleaf	0.61	Donald Lehmann	1.00	Wayne Desarbo	0.88
Peter Lenk	0.54	Robert Meyer	0.60	Joel Huber	0.87	Wagner Kamakura	0.85
Neeraj Arora	0.38	Jordan Louviere	0.59	Joel Steckel	0.81	Carl Mela	0.72
Rich Johnson	0.34	Tulin Erdem	0.55	Sunil Gupta	0.81	Michel Wedel	0.70
Terry Elrod	0.34	Andrew Mitchell	0.47	Barbara Kahn	0.75	Scott Neslin	0.63
Joan Walker	0.31	Dipankar Chakravarti	0.46	Richard Staelin	0.67	Kannan Srinivasan	0.57
Albert Bemmaor	0.30	Teck Ho	0.44	Russell Winer	0.60	Vijay Mahajan	0.57
Dan Horsky	0.28	Amit Pazgal	0.38	Arvind Rangaswamy	0.54	Asim Ansari	0.53
Greg Allenby	0.27	Michael Keane	0.32	Wesley Hutchinson	0.51	Pradeep Chintagunta	0.53
Daniel McFadden	0.27	Michael Rothkopf	0.32	Eric Johnson	0.50	Dick Wittink	0.48
Peter Rossi	0.27	Richard Bagozzi	0.32	Joseph Alba	0.50	Kamel Jedidi	0.43
Ben Akiva	0.25	Amnon Rapoport	0.29	David Bell	0.49	Venkatram Ramaswamy	0.43
Thomas Eagle	0.20	Amar Cheema	0.28	Edward Russo	0.47	Puneet Manchanda	0.41
Elie Ofek	0.20	James Cox	0.27	Anand Bodapati	0.47	Leonard Lodish	0.40
Jaehwan Kim	0.19	Joffre Swait	0.25	Gary Russell	0.46	Prasad Naik	0.39
Geraldine Fennell	0.19	David Hensher	0.24	Eric Bradlow	0.44	Paul Green	0.36
Sha Yang	0.18	Steven Lippman	0.24	Morris Holbrook	0.44	Yoram Wind	0.35
Thomas Otter	0.18	Rami Zwick	0.24	Fred Feinberg	0.41	Peter Verhoef	0.34
Bryan Orme	0.18	Richard Carson	0.24	John Little	0.40	Jehoshua Eliashberg	0.34
Tim Gilbride	0.18	Itzhak Gilboa	0.23	Randolph Bucklin	0.40	Baohong Sun	0.32
Tommy Garling	0.17	Joydeep Srivastava	0.23	Aradhna Krishna	0.38	Ajith Kumar	0.29
Norbert Schwarz	0.16	Atanu Sinha	0.21	Allan Shocker	0.38	Raghuram Iyengar	0.29
Avg. centrality	0.04	Avg. centrality	0.03	Avg. centrality	0.04	Avg. centrality	0.04
Avg. publications	2.53	Avg. publications	2.94	Avg. publications	3.96	Avg. publications	3.96
Avg. coauthors	5.92	Avg. coauthors	4.69	Avg. coauthors	5.59	Avg. coauthors	5.30

N=30,897 (Goldenberg et al. [10] sample); N=128 (promotion sample)

Table 4 Research characteristics of modelers in promotion sample associated with coauthorship communities

	Community 1	Community 2	Community 3	Community 4	Others
Avg. Publications Tier 1	3.71	4.09	4.07	3.30	2.67
Avg. Publications Tier 2	1.86	2.09	1.37	1.23	0.86
Avg. Publications Tier 3	0.29	1.09	0.78	0.63	0.93
Avg. Publications Tier 4	1.29	1.18	0.93	0.95	1.40
Avg. Num. Coauthors	30.79	3.39	3.20	3.11	2.82

N=128 (Promotion sample)

4 Determinants of Promotion and Time to Promotion

In this section, we investigate the factors[6] that determine modelers' promotion and time to promotion. We will first assess whether early signals of job market attractiveness (i.e., what was known at the time of first hire) are associated with future promotion. Next, we will use all known information on modelers to predict promotion and time to promotion. Finally, we will discuss the value of different research portfolios in different hiring departments and discuss how membership in coauthorship networks and prestige substantially improve the probability of promotion.

Our approach to analysis is as follows. We model the probability of promotion using logistic regression analysis and time to promotion using survival analysis. For the latter analysis, we employ a proportional hazard Cox regression [6] in which non-censored observations are those modelers who were promoted and right-censored observations are those modelers who were not. Thus, our failure variable is promotion, and positive estimates or hazard ratios imply an increase in "risk" of being promoted and should be judged as positive factors towards promotion. Tied uncensored observations are resolved using the Breslow method [5].

4.1 Does Early Job Market Attractiveness Predict Promotion and Time to Promotion?

An implicit assumption in the entry-level job market is that attractive job candidates remain attractive after being hired. Signals of early job market attractiveness include whether the degree-granting department is prestigious (i.e. top 30), as this suggests future research productivity [2] and exceptional productivity in the leading journals, an important criterion for promotion [21] that may help hiring departments bolster or solidify their rankings [11].

We test this implicit assumption by relating promotion and time to promotion to the signals observable at the time of first hire. Thus, the objective of these models is to determine whether signals observed in the entry-level job market can be related to future promotion and time to promotion. Note that, for this reason, information on which hiring department the modeler started at cannot be incorporated into the model as this information is revealed afterwards. Similarly, because a candidate's social connections may not be developed enough at this stage, we also omit coauthorship community variables from this analysis. Finally, because only one top tier 4 publication was observed prior to hiring, we do not divide tier 4 publications into "top" and "other" for this analysis. Results are shown in Table 5.

The first set of results in Table 5 shows the influence of modelers' early job market signals on promotion.[7] For each model, two sets of estimates are shown. The first set includes regression coefficients, while the second set includes odds ratios (for promotion models) or hazard ratios (for time to promotion models). These ratios measure the increase in odds of being promoted when the variable in question takes the value of 1, as compared to the case where it takes the value of 0 [12], and can be interpreted as the number of times the modeler with the variable with the value of 1 is more likely to be promoted as compared to the modeler with the value of 0, everything else constant. Standard errors are shown in parentheses.

In general, we find that early job market attractiveness is not a very strong predictor of future promotion or time to

[6] Note that neither of the correlations among the explanatory variables as shown in Table 2 and 3 appears to indicate the possibility of a multicollinearity problem; to further assess this potential issue, we calculated the variance inflation factor (VIF) of each of the explanatory variables used in our subsequent analysis. None of the explanatory variables exceeds the usual level for concern, e.g., VIF≥5, with the highest VIF amounting to 4.11, and the average VIF among all explanatory variables amounting to 1.59.

[7] A possible additional factor that could influence promotion and time to promotion is modelers' years in the Ph.D. program before graduation, as there appears to be a trend towards lengthening time in the Ph.D. program. We gathered information on years spent in the Ph.D. program for 99 modelers in our promotion dataset. The results of our analyses are robust to including such variable, and furthermore, we find that time spent in the Ph.D. program does not influence a modeler's chance of promotion and time to promotion.

Table 5 Determinants of modelers' promotion and time to promotion, 1997–2005

		Effect of early job market signals				Effect of full information			
		Model 1 promotion		Model 2 time to promotion		Model 3 promotion		Model 4 time to promotion	
	Variable	Estimate	Odds ratio	Estimate	Hazard ratio	Estimate	Odds ratio	Estimate	Hazard ratio
Degree-granting department variables	Top 30 department	0.51 (0.74)	1.66	0.23 (0.36)	1.26	0.32 (0.56)	1.38	0.01 (0.39)	1.01
	Private department	−0.18 (0.49)	0.83	0.07 (0.23)	1.07	0.08 (0.42)	1.09	−0.13 (0.25)	0.88
Hiring department variables	Top 30 department	–	–	–	–	−0.32 (0.48)	0.72	0.12 (0.31)	1.12
	Private department	–	–	–	–	0.73[a] (0.40)	2.08	0.07 (0.30)	1.07
	Dept. offers Ph.D.	–	–	–	–	0.11 (0.57)	1.11	0.07 (0.36)	1.07
	Department in the USA	–	–	–	–	1.54[b] (0.53)	0.21	0.35 (0.42)	1.41
Candidate variables	Pubs. tier 1	0.67 (0.69)	1.95	0.29[a] (0.17)	1.34	0.70[b] (0.16)	2.00	0.09[a] (0.05)	1.10
	Pubs. tier 2	−0.00 (0.80)	1.00	0.15 (0.28)	1.17	0.48[a] (0.25)	1.61	0.07 (0.09)	1.07
	Pubs. tier 3	0.22 (0.53)	1.25	0.12 (0.14)	1.13	0.19 (0.21)	1.21	−0.05 (0.08)	0.95
	Pubs. top tier 4	–	–	–	–	1.06[b] (0.48)	2.88	0.12 (0.21)	1.13
	Pubs. other tier 4	−0.25 (0.33)	0.78	−0.11 (0.21)	0.90	0.46[b] (0.21)	1.58	−0.01 (0.08)	0.99
	Avg. coauthors	0.30[a] (0.18)	1.35	0.08 (0.06)	1.08	−0.01 (0.06)	0.99	0.06 (0.13)	1.07
	Male modeler	0.89[a] (0.50)	2.42	0.41 (0.27)	1.51	0.24 (0.40)	1.28	0.48[a] (0.28)	1.61
	Modeler from the USA	−0.46 (0.55)	0.63	−0.35 (0.31)	0.70	−0.28 (0.52)	0.76	−0.26 (0.31)	0.77
Coauthorship community variables	Community 1	–	–	–	–	0.77 (0.92)	2.16	0.41 (0.53)	1.50
	Community 2	–	–	–	–	0.17 (0.79)	1.19	0.29 (0.44)	1.33
	Community 3	–	–	–	–	0.13 (0.47)	1.13	0.28 (0.32)	1.32
	Community 4	–	–	–	–	0.83[a] (0.48)	2.29	0.70[b] (0.28)	2.02
	Intercept	−0.12 (0.80)	–	–	–	−1.99[b] (0.78)	–	–	–
	Log-likelihood	−61.99		−422.22		−97.41		−418.82	
	Pseudo-R^2	9.49 %		11.17 %		31.07 %		15.76 %	
	N	128		128		204		128	

N=128 (modelers); N=204 (positions taken by modelers). Note on full-information models: Full information promotion model includes dummy variables instead of percentages as hiring department covariates. Note on early signals models: Publications in tier 4 are not subdivided into "top" and "other" in these models

[a] Significant estimates 90 %

[b] Significant estimates 95 %

promotion. Indeed, the predictive power[8] of both models is quite low, with the promotion model (model 1) exhibiting an R^2 of 9.49 % and the time to promotion model (model 2) yielding an R^2 of 11.17 %. As to the factors that influence our dependent variables, we find that the average number of authors in modelers' publications before graduation, and being male, increase the probability of promotion. Of particular interest are critical factors such as early research productivity in tier 1 journals and top 30 status. Despite being important determinants of early job market attractiveness and hiring department utility in the marketing job market [24], we find that these factors do not influence the probability that a modeler may achieve promotion after being hired. However, we find that tier 1 publications do influence time to promotion, albeit marginally so.

4.2 Promotion and Time to Promotion Analysis Using Full Information

We now assess the determinants of promotion and time to promotion with all available information. For promotion, we assess the probability of a modeler being promoted at the *employment level*. This means that each data point in our dataset represents a particular hiring department where each modeler worked—a unique scholar-hiring department combination. Because a number of modelers in the promotion

[8] To determine the predictive power of our models, a pseudo- R^2 metric was computed [7, 13, 14]. An alternative approach is to utilize a holdout data to determine a percentage of correctly predicted observations. However, we do not use this approach as we have observations on modelers up to the present year.

dataset worked in more than one department, the number of observations increases from 128 to 204.

An interesting case to consider when assembling data at the employment level is when a modeler moves from department A (without promotion) to department B (with promotion). For each of these "promotion movements," two data points are included in our promotion dataset. The first data point includes the modeler's research productivity at department A and the characteristics of such department, with the dependent variable indicating no promotion; the second data point includes the *same* research productivity as in the case above, and the characteristics of department B, with the dependent variable indicating promotion.[9]

Research productivity when considering data at the employment level is measured with the number of articles published when employed at each particular department.[10] Dummy variables are used to indicate the type of hiring department modelers were employed in. In both specifications, the coauthorship community variables are also included as dummy variables. Therefore, the estimates of the community membership dummy variables should be interpreted as the effect of belonging to these communities on promotion and time to promotion with respect to modelers who belong to other, smaller communities, or those who do not belong to any.

For the analysis of time to promotion, we retain the original formulation used in model 2. That is, we analyze the data at the candidate level and use 128 observations. The reason to continue using this original formulation is that the inclusion of "promotion moves" can lead to an important confound when examining time to promotion. Specifically, a modeler may have moved from one department to another because of a promotion. Whereas in the promotion model, one can classify the first department as a "no promotion" and the second as a promotion, then keep the modeler's publication portfolio equal at both departments; for time to promotion, it is unclear what time value to assign to the second move. Results of the promotion (model 3) and time to promotion (model 4) analyses with full information are also shown in Table 5.

Regarding the probability of promotion, we find that working in a department within the USA, as opposed to working overseas, implies that modelers are 79 % less likely to be promoted. This means that, conversely, modelers have a much higher likelihood of promotion in international departments. In addition, we find evidence (albeit at the 10 % significance level) that modelers are 2.08 times more likely to be promoted if they are employed in a private hiring department as compared to a public hiring department, on average. As to research productivity, we find evidence that tier 1, tier 2, and tier 4 publications increase promotion probability. Candidates with a tier 1 publication are twice as likely to be promoted than those who do not have one, and candidates with a tier 2 publication are 61 % more likely to be promoted. Interestingly, we find the effect of top tier 4 publications to be quite substantial. To be specific, candidates with a top tier 4 publication are 2.88 times more likely to be promoted as candidates who do not have such a publication. However, care must be exercised when interpreting this estimate, as the number of candidates with top tier 4 publications is relatively low.

As to the impact of coauthorship, we find that membership in one of the communities found using the Louvain community detection algorithm has a significant (at the 10 % level) effect on promotion: modelers who belong to coauthorship community 4 are 2.29 times more likely to be promoted as compared to modelers that do not belong to this community. Finally, when comparing the full-information promotion model (model 3) to the early job market promotion model (model 1), we observe an increase in predictive power, obtaining an R^2 of 31.07 %. This implies that as modelers' academic career unfolds, valuable, additional signals that can aid predicting the probability of promotion emerge.

Regarding time to promotion, we find that few variables are statistically significant, as in our analysis of early job market attractiveness. Furthermore, predictive power remains quite poor, with an R^2 of 15.76 %. However, we find evidence (at the 10 % significance level) that tier 1 publications again accelerate time to promotion. For each tier 1 publication, the likelihood of promotion increases by 10 %. Furthermore, male modelers, on average, are promoted faster, implying a 62 % increase in probability of promotion. Finally, we find that belonging to coauthorship community 4 influences time to promotion as well, such that, similar to promotion, membership in this community almost doubles the chance of being promoted.

4.3 The Value of Research Portfolios at Different Hiring Departments

A modeler's publication portfolio may be valued differently for promotion at different hiring departments. If so, modelers may need to adjust their research portfolio or target journals as they move from one type of department to another. Thus, we next investigate the impact of modelers' publication record on the probability of promotion at departments that offer a Ph.D. program as compared to those who do not. Because of the low incidence of top tier 4 publications from modelers in hiring departments without a Ph.D. program, we do not divide tier 4 publications into top and other for this analysis. Results are shown in Table 6.

We find that the effect of modelers' publication portfolios on promotion is substantially different at departments who

[9] Note that the results of the analyses that use these "promotion movements" are robust to removing modelers that were observed to make such moves.

[10] These results are robust to using a cumulative specification in which the number of total publications a modeler had up to the last year of employment as assistant professor at each department are used instead.

have a Ph.D. program, as compared to others. For departments with a Ph.D. program, the qualitative nature of the results in Table 5 holds, although the magnitudes are different. Importantly, tier 4 publications now are observed to exceed the value of tier 1 publications. Notice that, counterintuitively, for departments without a Ph.D. program, only tier 1 publications influence promotion, this at the 10 % significance level. Finally, notice that the effect of coauthorship community 4 is also present (again, at the 10 % significance level), which suggests that being a member of this coauthorship social network is a robust predictor of promotion.

4.4 Predicting Modelers' Probability of Promotion

The analysis shown so far is valuable in that it isolates the main factors associated with modelers' promotion outcomes. However, it is also important to predict these outcomes given modelers' characteristics as well as those of the departments they graduated from and those they work in. As such, we present a brief predictive analysis of promotion scenarios by focusing on the role of research productivity, prestige, and coauthorship on modelers' predicted probability of promotion. Note that given the low predictive power of the time to promotion models shown in Table 5, we focus on predicting the probability of promotion only.

Consider a modeler who does not come from a top 30 degree-granting department, is unconnected with the four major coauthorship communities discussed earlier, and has no publications in his portfolio. Furthermore, given the characteristics of the average modeler, assume this modeler is male, from a private degree-granting department, and was an international student (not from the US). We call this modeler the "benchmark" modeler. Given the results shown in Tables 5 and 6, a counterfactual modeler with more publications, prestige, or member of a coauthorship network should be expected to be more likely to be promoted than the benchmark modeler.

Utilizing the regression results from model 5, we estimated modelers' probability of promotion at a Ph.D. granting, private university, which is a common first place of employment among modelers. We find that the predicted promotion probability for the benchmark modeler is 13.24 %. If the benchmark modeler, instead, studied at a top 30 degree-granting department, the predicted probability of promotion increases to 19.65 %. If, in addition, the modeler were also a member of

Table 6 Model 5: the effect of modelers' research on the probability of promotion at departments with/without Ph.D. program, 1997–2005

		Variable	Estimate	Odds ratio
Degree-granting department variables		Top 30 departments	0.39 (0.59)	1.48
		Private department	0.07 (0.46)	1.08
Hiring department variables		Top 30 departments	−0.40 (0.46)	0.67
		Private department	0.86^{b} (0.42)	2.37
		Dept. with Ph.D. program	−1.09 (0.78)	0.34
		Department in the USA	−1.54 (0.54)	0.21
Candidate variables (with moderation effect)	Employment at department with Ph.D. program	Publications tier 1	0.75^{b} (0.15)	2.12
		Publications tier 2	0.53^{b} (0.25)	1.70
		Publications tier 3	0.36 (0.23)	1.44
		Publications tier 4	0.80^{b} (0.23)	2.24
	Employment atdepartment without Ph.D. program	Publications tier 1	0.59^{a} (0.34)	1.81
		Publications tier 2	0.40 (0.43)	1.50
		Publications tier 3	0.27 (0.41)	1.31
		Publications tier 4	−0.22 (0.52)	0.80
Candidate variables (no moderation)		Avg. no. of coauthors	−0.003 (0.05)	1.00
		Male modeler	0.17 (0.39)	1.18
		Modeler from the USA	−0.21 (0.51)	0.80
Coauthorship community variables		Community 1	0.56 (0.91)	1.75
		Community 2	0.17 (0.82)	1.19
		Community 3	0.005 (0.48)	1.01
		Community 4	0.87^{b} (0.46)	2.40
		Intercept	−1.23 (0.88)	0.29
		Log-likelihood	−95.35	
		Pseudo-R^2	32.52 %	
		N	204	

N=204 (positions took by modelers).Publications in tier 4 are not subdivided into "top" and "other" in this model

[a] Significant estimates 90 %

[b] Significant estimates 95 %

coauthorship community 4 (which we call a "prestigious and connected" modeler), the predicted probability of promotion exhibits a further increase to 38.10 %. This highlights the fact that, in hiring departments with a Ph.D. granting department, the advantages determined by modelers' degree-granting department prestige and embeddedness into particular coauthorship networks can potentially increase the predicted probability of promotion by more than 20 %.

We also investigated the impact of a high research productivity on the probability of promotion. To be specific, we deem a high research productivity to be four published tier 1 articles, as the average across all promoted modelers was 3.45 tier 1 publications, as shown in Table 1. With such a publication portfolio, the probability of promotion for a benchmark modeler is 75.41 %; for a prestigious modeler, it is 83.09 %; and for a prestigious and connected modeler, it is 92.51 %. These results highlight that the advantages enjoyed by modelers from prestigious degree-granting departments or who are well connected, persist even when their peers exhibit the same level of research productivity.

5 Discussion

In this article, we investigate the determinants of promotion and time to promotion for modeling scholars. Specifically, we relate these outcomes to (1) signals of early job market attractiveness and (2) modelers' full history, including their coauthorship network memberships and research portfolio. We control for department and demographic characteristics as well. Further, we address whether a modeler's publication portfolio may impact promotion differently in departments that offer a Ph.D. program, as compared to departments that do not offer such programs. Our analysis is first in the literature to address multiple determinants of promotion simultaneously as well as to assess whether early signals of job market attractiveness influence future promotion. We find valuable implications for hiring departments and modelers both in the market and on the tenure-track, which we discuss next.

We find that some, but not all, hiring department characteristics impact promotion; none impact time to promotion. For modelers, working in a marketing department outside of the USA, and on a private department, implies a higher probability of being promoted. It is interesting to note that the top 30 status of a degree-granting department does not influence either promotion or time to promotion. This suggests that a candidate's "pedigree," which is a key driver of early job market attractiveness [2, 24], may not translate to future success as far as promotion goes. However, it could be that most candidates with pedigree are hired at similarly prestigious positions, such that, for those candidates, it is harder to obtain first promotion. We believe a larger sample would shed light into this issue. More generally, we suggest that factors such as pedigree be evaluated in tandem with other factors, such as modelers' publication record and social connections, so as to form a richer picture of the candidate and his future potential.

To this last point, we find that tier 1 publications positively influence both promotion and time to promotion. However, we find that tier 2 and tier 4 publications also influence the probability of promotion. This is surprising, as earlier work has shown that publications outside of tier 1 do not influence job market outcomes in general [8] and that, for modelers in particular, tier 4 publications can even diminish these outcomes [24]. Our results highlight that, after graduation, modelers can publish in a wider assortment of research outlets and still be promoted. But, after addressing the moderating effect of being employed in a department that offers a Ph.D. program, this advice holds only for these departments. In the case of departments that do not offer such programs, targeting rier 1 journals consistently seems to be more conducive to promotion. An interesting extension to our results would be to determine whether different *combinations* of publications in different tiers are associated with tenure, to determine whether these may complement each other.

We also find evidence that coauthorship, after controlling for the particular journal tiers in which modelers published, also increases the probability of promotion. A larger number of authors, on average, is a signal of promotion at the job market stage. This implies that, for a junior modeler, being well connected in terms of *number* of social connections, or level of coauthorship, is a positive early signal. However, in the tenure-track, this effect does not hold—instead, there is a strong positive effect due to coauthorship community membership. This means that, once a junior modeler becomes an established faculty, being well connected in terms of the *specific community* he or she belongs to becomes an important determinant of promotion. Aside for the implications this has for marketing academia, we believe these results point out the need to include social network membership variables into empirical analyses of social networks.

The present work has some limitations. Our sample, by definition, is truncated (and quite small) because it includes only modelers. Including other scholars, such as those specialized in consumer behavior or strategy, and addressing the determinants of promotion and time to promotion for each of these as well would be a worthwhile extension of our work—in this issue, Rajiv and colleagues [19] tackle this important problem, focusing on research productivity. Also, we take a reduced-form approach to analysis, instead of developing a more sophisticated matching model. This is because in the entry-level marketing job market, as the market unfolds in well-established periods every year, constructing job markets is feasible [23]. However, in the tenure-track job market, where interactions between hiring departments and potential candidates occur throughout the year, the periodicity of the market is broken, which does not satisfy the condition that markets be well defined [20]. Furthermore, we must acknowledge a potential endogeneity issue. Our coauthorship community variables are dummy variables that represent a "snapshot" of coauthorship networks up to 2007. But, it could be that the characteristics associated with promotion and time to promotion also influence the likelihood that one belongs to important coauthorship communities, necessitating a different model that incorporates network formation as an additional dependent variable. We believe such a model would represent a significant, future contribution. Finally, a finer analysis delving into the differences in promotion and time to promotion outcomes for different types of modelers (i.e., analytical vs. empirical) might yield valuable additional insights.

Ultimately, understanding the factors that drive promotion can help modelers better develop their own research portfolios and social connections to increase their chances of success. For hiring departments, understanding these factors as well as the useful summary metrics they can use to assess attractiveness can help in better recruiting and selecting modeling scholars. We believe this article serves as a first step in achieving these goals and invites further empirical work into the determinants of promotion and time to promotion.

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