Understanding Co-Authorship among Consumer Behavior Scholars

Neil Bendle, Xin (Shane) Wang and Feng Mai

Purpose of the Study: To understand co-authorship habits among a set of consumer behavior scholars. We analyze the consumer behavior community and shed light on why these scholars co-author.

Method/Design and Sample: Our data covers all issues of the Journal of Consumer Psychology and the Journal of Consumer Research to December 2014, totaling 2,698 articles with 5,951 author credits. We describe the data and community characteristics. We advance the literature by using modern social network analysis techniques to map a social network and provide social network metrics across two journals using over 40 years of data.

Results: We show the distribution of authorship of papers, highlight co-authorship habits, and illustrate rising co-authorship over time. We reveal the most connected scholars, and those with critical connections. The community is surprisingly coherent; while most only publish one paper, 72% of scholars are connected by co-authorship. We highlight what we term *active collaboration* between the hyper-productive scholars, and demonstrate how inter-generational collaboration works through a school's network.

Value to Marketing Educators: Marketing educators will benefit from the descriptive data we provide to aid administrative and career decisions. We show the network of co-authorship and provide benchmarks for marketing academics. We illustrate that consumer behavior is a meaningful community and provide evidence why scholars collaborate.

Keywords: Social Network Analysis; Consumer Behavior; Co-authorship; Measurement of Scholarship

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Introduction to Consumer Behavior Co-Authorships. We record the entire social network of 2,404 scholars publishing in the *Journal of Consumer Research* (JCR) and the *Journal of Consumer Psychology* (JCP). Our research uses more data points over a longer period of time than any prior work, and combines this information with modern social network techniques to document the social network of consumer behavior scholars. We give evidence for the existence of such a community and investigate the community's publications habits. Incredibly, 72% of all scholars in the network are linked by co-authorship, despite most scholars only publishing once. We note what we call *active collaboration* between the most productive scholars, and highlight advisor and student relationships at a single school.

LITERATURE REVIEW

The work of academic marketers is an important research area (Gray, Peltier, & Schibrowsky, 2012) and their co-authorship matters. Indeed, the challenge of choosing a co-author arose in the first issue of this journal (Borin, 2001; Kurtz, 2001). Why scholars co-author remains poorly understood. *Division of labor* has been suggested as a plausible motivation; greater focus means specialized skills must be brought onto the team. The recruited scholars, seeing the *opportunity costs of time* for supplying their skills, demand authorship credit. Furthermore, as greater *quality* is demanded, perhaps scholars must increase the level of talent on the team.

The randomness involved in the review process means *diversification* can help. Putting 50% effort into two papers and sharing the credit is safer than putting 100% into a single paper (Barnett, Ault, & Kaserman, 1988). Less positive is the idea of *gift authorship*—gaming by scholars who swap credit to mutually improve their resumes (Henriksen, 2015). Co-authorship is a source of conflict and ethical problems (Marušić, Bošnjak, & Jerončić, 2011) and the mutual dependence of scholars—especially Ph.D. students and their advisors—has been shown quite clearly (Schroeder, Langrehr, & Floyd, 1995). We follow Brown, Chan, & Lai (2006) in examining the issue using secondary (publication) data. Therefore, we cannot definitively answer why scholars make the decision to co-author (undoubtedly, there are multiple factors), but we can provide some insight into why it might occur.

We ally the co-authorship literature with the rapidly growing field of social network analysis (Eaton, Ward, Kumar, & Reingen, 1999; Morlacchi, Wilkinson, & Young, 2005) to understand a scientific discovery network (Newman, 2001). The marketing social network literature identifies the most influential players in any given social grouping (Goldenberg, Han, Lehmann, & Hong, 2009; Trusov, Bodapati, & Bucklin, 2010) and we provide this information for the consumer behavior community. We use the idea of "invisible colleges" (Eaton et al., 1999) to consider whether or not scholars organize into discrete groups of specialists. Mapping the entire social network of consumer behavior scholars allows us to better understand whether the community is even a meaningful construct.

SOCIAL NETWORK ANALYSIS

Social network analysis focuses on understanding connections between people. One of its most important applications is in epidemiology; health professionals look at the links between people to see how communicable diseases spread (Christakis & Fowler, 2011). Sociological research uses the technique to develop mathematical explanations of group behavior (Scott, 1988) as does research on organizations (Tichy, Tushman, & Fombrun, 1979). In politics we can visualize political polarization from relationships between lawmakers of different parties (Christakis & Fowler, 2011). The technique is richly descriptive but it also allows us to better understand phenomenon that are theoretically interesting, such as the transmission of ideas between people (Borgatti, Mehra, Brass, & Labianca, 2009). The underlying notion is that analyzing an entire network tell us something beyond what we can observe from analyzing only the members of the network. In business and sports the team is more than the sum of its parts.

Using social network analysis a workplace can, for example, be mapped as a series of links using email correspondence. We can note who never interacts and those who work closely together. The scholar might survey self-reported friendships to see the overlap between these and working relationships and seek to understand how information is transmitted through formal and informal ties. Alternatively the study might reveal who are the key members of staff who connect, for example, the marketing and accounting groups. (The ability to connect up disparate groups is captured by a person's betweenness centrality, a metric we will discuss later).

In studying networks sometimes the boundary will be relatively easy to specify, e.g., an organization's workers might be relatively easy to define. (Although even here organizational boundaries can be fuzzy regarding freelancers, consultants, or outsourced functions). In other networks, such as a community of academic researchers, the appropriate boundary can be challenging to specify given the community is permeable and its members only informally connected. Furthermore, networks change over time and often massively interconnect with other networks.

Social network analysis' popularity may be rising due to increasing access to data and computing power. Offline network research often involves laboriously collecting self-reports (Knoke & Yang, 2010) which traditionally was followed by intricate manual visualization. Nowadays online collection allows access to a massive number of connections relatively simply. One can capture networks on Facebook, Twitter, links between websites, and track relationships among Wiki editors (Hansen, Shneiderman, & Smith, 2010) and quickly visualize these with widely available software.

The main reason for the growth of social network research (Borgatti et al., 2009) is its ability to deliver novel insights. To see the benefit of studying networks consider three layers of analysis. The first is the individual and his or her personal characteristics, e.g., Jamie is 45. This level of data is often used in academic research. The next level contains characteristics tied to a person but that only arise because someone else is involved, e.g., Jamie and Chris are married. These characteristics are sometimes considered in academic research but are especially easy to note in a social network analysis given we record relationships. Finally, there are properties that cannot be connected to any single network member; properties that arise from the linkages amongst the network as a whole. The village that Jamie and Chris live in is highly interconnected as everyone knows everyone else. Villagers have the connections but the village itself has the property of being densely interconnected. This perspective can only be captured by considering the network as a whole and so is arguably the unique benefit of social network analysis.

Thus, while network data will typically contain personal characteristics, and the analysis will reveal interactions it is observing at the network level which generates the most unique insights. By mapping the entire network's relationships we can measure and visualize the network's properties. Using this visualization we can assess how diseases, good ideas, bad habits, or anything else might impact the network.

OVERVIEW OF RESEARCH QUESTIONS

We answer four specific research questions about the consumer behavior community. Firstly, we want to better understand the publication habits of those in the consumer behavior community (Eaton et al., 1999; Morlacchi et al., 2005). We then turn to describing the nature of the community using modern social network analysis tools. These first two aims allow us to be understand the community and its habits.

Academics and administrators will be especially interested in learning about those who publish extensively in the community so next we drill down to better understand the characteristics of those who are productive in our dataset. We can see both their individual characteristics and their relationships, (which by definition involve others as well as the focal person). Social network analysis also allows us to explore what the structure of the community implies. To assess this we take an initial look at whether schools are sources of connections. This will help administrators justify the value of their PhD programs (Elbeck & Schee, 2014). The programs can be seen not just to be a source of alumni and co-authors. Additionally because the community is so densely connected PhD programs link the school with a range of researchers who never trained at the school.

R1. What are the publications habits of the community?
R2. What does the community look like and is it even a meaningful construct?
R3. What are the characteristics of successful scholars?
R4. Can we see schools as sources of connections?

METHODOLOGY

Our Data

We examine publications in two exclusively consumer-focused journals, JCR and JCP. This is a limitation, as we omit relevant articles that are a) published in other consumer behavior journals (e.g., Psychology and Marketing), b) published in journals with broader focus (e.g., Journal of Marketing Research), and/or c) published in any other ways that create knowledge (cases, books, etc.). Restricting analysis to JCR and JCP, however, allows us to avoid questions around whether work in a non-exclusively consumer-focused journal should be classified as consumer research. Given that JCR and JCP are on the FT45 list, this restriction also means that quality should be relatively comparable between the papers in our dataset.

Our unique dataset is based on the downloaded details of all papers from the creation of JCR (1974) and JCP (1992) until the end of 2014—volume 41 (24), issue 4 (4) for JCR (JCP). We used JSTOR Data for Research (dfr.jstor.org) which provided us with article metadata such as Title, Abstract, Author(s), Volume, Issue, and Publication Date. This allowed us to create a database of all the authors who had published in the two journals in the period. A major challenge is ensuring that each author is represented by only one record. Thus, we reviewed the data using simple programs and visual inspection looking for authors who had two records, such as those scholars who sometimes publish with a middle initial and sometimes don’t. We also checked for name changes (e.g., upon marriage) by visiting scholars’ websites and interviewing colleagues. Through this we aggregated our data for each scholar under a single name.

This list shows the value of being able to use many years of data as we do -- exceptional scholars add to their publications for many years. For example, Donald Lehman has 40 years between his first and last papers in our data.

Journal publications vary from research articles through to “editorial notes” and “in memoriam” pieces. Similar to Wang, Bendle, Mai, and Cotte (2015), we examined only “research related articles with an abstract” by removing details of any articles that did not have an abstract. JCR (JCP) published 1,941 (757) such articles from the journal’s inception to the end of 2014, meaning our dataset contains 2,698 articles. These articles contain 4,190 (1,761) author credits in the JCR (JCP) data, giving 2.16 (2.33) authors per JCR (JCP) article. Multiple publications per individual means 1,844 (1,037) unique individuals have published in JCR (JCP). 0 describes the dataset and distribution of papers per scholar. We used the database we created to perform various queries on the data.

Table 1: Data Summary

Panel A: Data Description

	JCP	JCR	Combined
Articles (A)	757	1941	2698
Author credits (B)	1761	4190	5951
Authors per paper (B/A)	2.33	2.16	2.21
Unique authors (C)	1037	1844	2404
Papers per author (B/C)	1.70	2.27	2.48
Standard deviation of publications per author	1.57	2.59	3.18

Panel B: Publications per Scholar

Number of Publications	Scholars With # of JCPs, (percentile of	Scholars With # of JCRs, (percentile of	Scholars With # of JCPs, (percentile of

	scholars), and total JCPs in italics		scholars), and total JCRs in italics		scholars), and total JCPs +JCRs in italics	
1	710 (68%)	*710*	1101 (60%)	*1101*	1434 (60%)	*1434*
2	172 (17%)	*344*	301 (16%)	*602*	375 (16%)	*750*
3	69 (7%)	*207*	138 (7%)	*414*	167 (7%)	*501*
4	42 (4%)	*168*	87 (5%)	*348*	112 (5%)	*448*
5	8 (1%)	*40*	66 (4%)	*330*	79 (3%)	*395*
6	14 (1%)	*84*	41 (2%)	*246*	59 (2%)	*354*
7	6 (1%)	*42*	23 (1%)	*161*	29 (1%)	*203*
8	6 (1%)	*48*	20 (1%)	*160*	30 (1%)	*240*
9	1 (0%)	*9*	18 (1%)	*162*	21 (1%)	*189*
10	5 (0%)	*50*	11 (1%)	*110*	19 (1%)	*190*
>10	4 (0%)	*59*	38 (2%)	*556*	79 (3%)	*1247*
	1,037 (100%)	*1761*	1,844 (100%)	*4190*	2,404 (100%)	*5951*

Analysis

In addition to some basic statistical testing we use social network analysis to visualize and describe the community. Social network analysis is a way of moving from the properties of the individual to considering the properties of the group. We can see three levels of analysis which can be captured.

The first level is describing an individual. In our dataset an example of this is a scholar's personal number of publications. It is something that relates to them, and not directly to anyone else.

A second level of analysis describes connections to others. This is measured by such metrics as the degree centrality; the number of links a scholar has to others. These connections capture the co-authorships that are vital to our study. Thus while a scholar's publications are a personal characteristic assessing the number of relationships they have, i.e. the number of scholars they have published with, requires others to be involved.

The final level of analysis is that which describes the network. This is not specifically related to any one individual but to the network as a whole. This level of analysis answers questions such as how linked up is this community?

Social network analysis is an approach that often relies on strong visuals. Modern analytical tools produce visual representations of the network. With a large number of linkages arrangement of the scholars in two dimensional space so one can clearly see the linkages between them can be challenging. Social network analysis programs will typically give default views but allow researchers to rearrange the placement of individuals to allow linkages to be more easily seen. Here we only supply visual representations of subsets of our data. The entire consumer research dataset is too large, and so the scholars and their linkages to messy, for the main picture to be easily interpreted. (This full picture is available from the authors upon request).

The visual representations allow us to see the connections between members of a network and how tightly packed the network is. Social network analysis also gives an array of metrics for clearer specification. We will examine a number of the more important metrics. As mentioned these come at three levels: individual, relationship, and community. The individual level includes a researcher's publications which is input from our database and is a characteristics of the node (i.e. individual scholar). Relationships are captured by linkages (edges) which connect individual scholars. Given multiple scholars must be involved these are not the sole characteristic of any single individual. Co-authorships are input from our data which the social network analytics tool visualizes. We calculate metrics for individuals based upon relationships such as betweenness centrality -- how vital any individual is to linking up a network. Finally, properties of the community emerge from the interaction of all its members but cannot be directly tied to any individual. These are measured with metrics such as graph density (the proportion of links that could be made that are made), and the size of the largest connected group.

We use all three of these levels to better understand the scholars and their community.

RESULTS

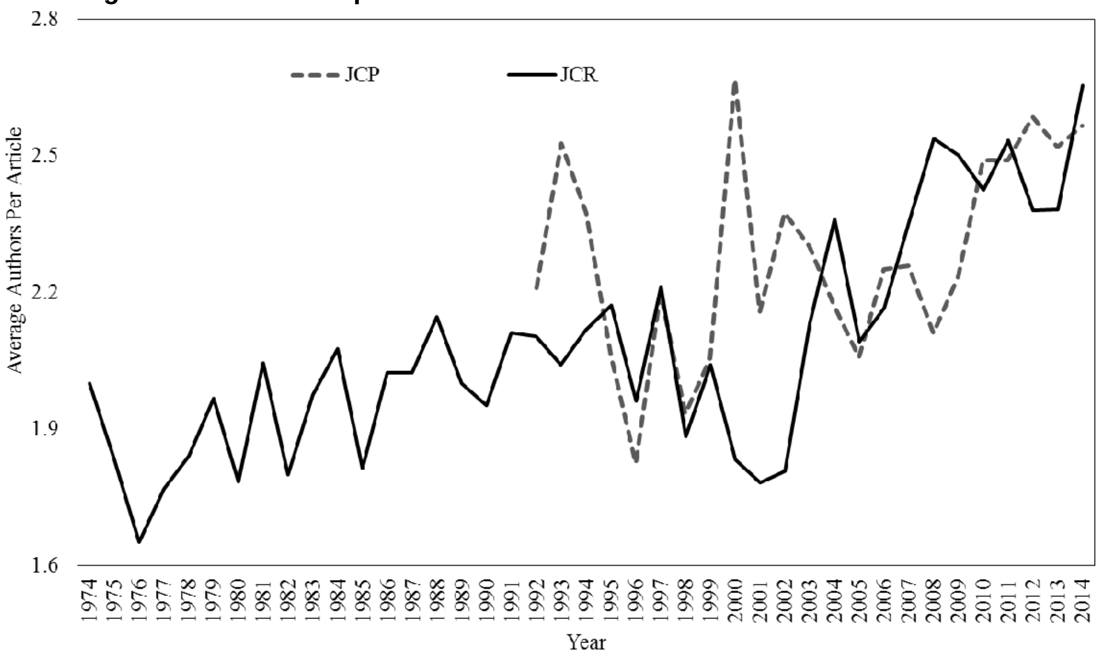
R1: What are the publications habits of the community?

Our measure of scholar productivity is articles published—a measure that typically has a long tail (Morlacchi et al., 2005). Lotka's rule suggests a skewed distribution (Eaton et al., 1999); most scholars publish only a few papers each, but a small number publish a large number of papers. Let $\pi_n = k\, n^{-2}$ where π_n is the proportion of scholars who have published *n* papers, and *k* is a constant. The proportion of scholars expected to have published a given number of papers (*n*) steeply declines with *n*.

For Lotka's rule to apply, the beta parameter on the regression $Log(\pi_n)=Log(k)-\beta Log(n^2)$ should be around -1. When β is more negative, the slope is greater (i.e., a smaller proportion of scholars publish a larger numbers of papers). In examining consumer behavior scholars, Eaton et al. (1999) found this parameter to be -1.159 with an adjusted R^2 of .930. Our JCR (JCP) data has a remarkably similar beta of -1.14 (-1.26) and an adjusted R^2 of .962 (.938). Combined, our data gives a beta parameter of -.825 and adjusted R^2 of .921. Therefore, the results generally support Lotka's rule.

In line with other researchers (Brown et al., 2006; Yang, Jaramillo, & Chonko, 2010), we find a trend towards increasing co-authorship (see Figure 1). This suggests that our data is representative of a wider trend within academia (Barnett et al., 1988; Henriksen, 2015).

Figure 1: Co-Authors per Article



To investigate why scholars choose to co-author, we regressed a scholar's productivity on his or her average number of co-authors. We controlled for the year of the author's first publication, as earlier papers tend to have fewer co-authors. Year of first publication is significant (β=-0.04, p<.01), but even controlling for this, more productive scholars tend to have fewer co-authors (β=-0.21, p<.01). Less productive (presumably less confident) scholars may feel the need to bring in outside help. The *opportunity cost of time* hypothesis suggests that those assisting will typically demand an author credit.

The average size of papers has increased over time (β=0.06, p<.001), so it is possible that increasing workload is driving increasing article size. We separated the JCP and JCR data—because the pattern of increase differs between journals—and regressed the number of co-authors on page length. Size significantly predicted co-authorship for JCR articles (β=0.01, p<.05), but not for JCP articles (β=0.002, p>.7). Escalating work per paper may be a factor in increasing co-authorships, but more research is needed.

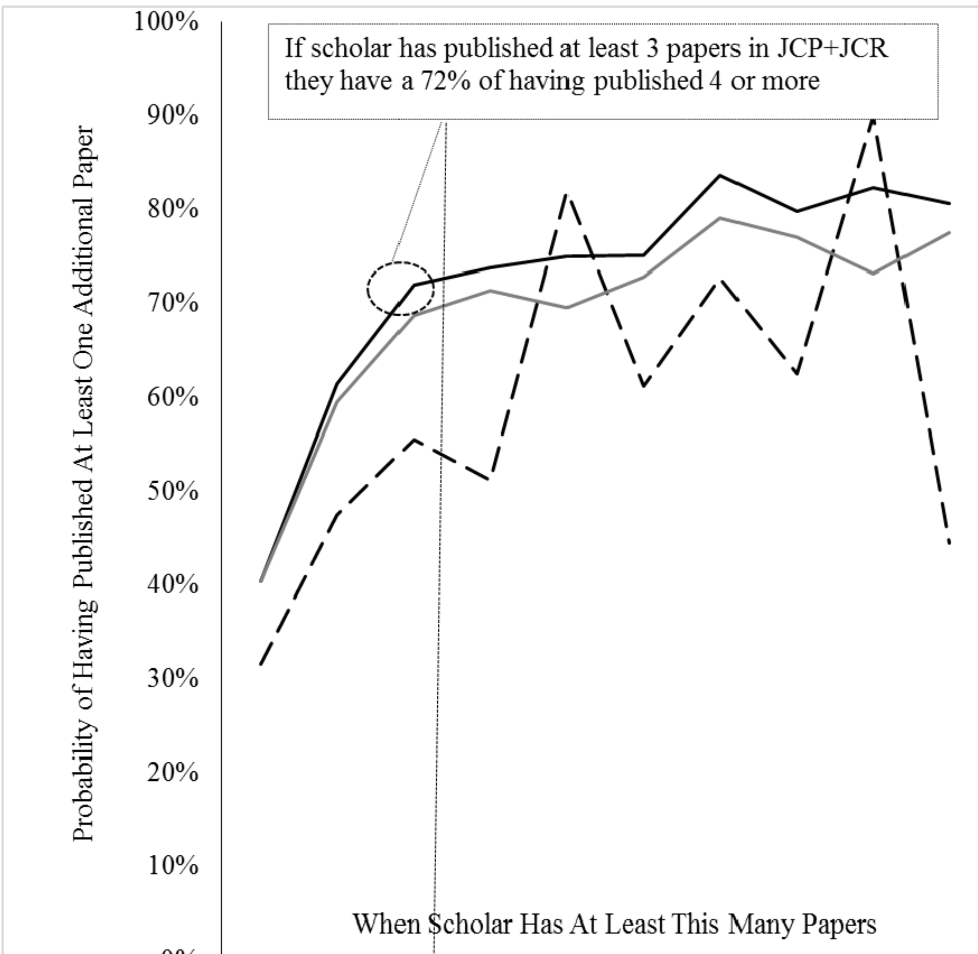
We wanted to test the *quality* hypothesis so we turned to a proxy for quality: citations. Unlike in a citation analysis (Chen, Song, Yuan, & Zhang, 2008; Leong, 1989), we are not interested in citations per se, but whether co-authorship increases citations. We regressed citations upon the number of co-authors, controlling for factors that may drive citations. Article size might matter to citations as larger articles have more content to cite. Publication year and the square of this term were added to capture the impact of year and non-linearity in temporal effects. (Recent papers usually have few citations, as scholars have not had time to cite them. Older papers also have fewer citations because there were fewer scholars citing when these papers were at the height of their impact.) We added a JCP dummy and controlled for author productivity—a proxy for researcher quality—using the average of the co-authors' publications. The number of scholars on the paper was the only *non-significant* factor (β=-2.5, p>.2). The evidence is limited, but what we have does not support the quality hypothesis.

This trend towards increasing co-authorship may explain why JCP articles have more authors (t(1239)=-4.1, p<.01). JCP articles are newer: the median JCP (JCR) article was published in 2007 (2000). If co-authorship is increasing across the board over time the relative recency of the average JCP article may explain why these articles have more authors, rather than some other characteristic of the journal. We regressed the number of authors on the year (1974=1 through to 2014=41) and added a dummy variable if the paper was in JCP. The JCP dummy does not predict the number of co-authors (β=.024, p>.5), but the year of publication does (β=.017, p<.001), with newer articles having more authors. Similar co-authorship levels on JCP and JCR articles (after controlling for year) support the idea of a single consumer behavior community, because relatively homogenous communities share co-authorship habits, but these habits differ between communities. For example, Newman (2001) notes differences among the number of co-authors by research field. Bio-medical and astrophysics articles have a high average number of co-authors per article (3.75 and 3.35 respectively), whereas theoretical high-energy physics articles only require 1.99 authors.

Predicted publication level matters in several ways. Authors want to calibrate their optimism about their personal publication level, while hiring institutions and promotion and tenure committees want to predict research productivity. Publications are not an end in themselves but they are a way for academics to gain impact, often measured in citations (Baumgartner, 2010; Stremersch, Camachoa, Vannestec, & Verniers, 2015), which affects how schools are assessed (Soutar, Wilkinson, & Young, 2015).

To help inform estimates of productivity, 0 maps the probability of a scholar having published at least one more paper when that scholar has at least a certain number of publications. We get the probability of further publications in our dataset given *n* publications using: $\frac{Number\ of\ Scholars\ with\ n+1\ Publications}{Number\ of\ Scholars\ with\ n\ Publications}$. For example, consider any scholar who has published at least three papers in the full dataset. 595 scholars have published 3 or more papers and 428 have published 4 or more. Reading from the y-axis shows that a randomly selected scholar with at least three papers has a 72% (428/595) of having published 4+ papers.

Figure 2: Probability of another Publication, Given Level of Publication



	1	2	3	4	5	6	7	8	9	10
JCP+JCR	40%	61%	72%	74%	75%	75%	84%	80%	82%	81%
JCP	32%	47%	55%	51%	82%	61%	73%	63%	90%	44%
JCR	40%	59%	69%	71%	70%	73%	79%	77%	73%	78%

As in *Marketing Science*, multiple publications are linked with further publications; "[t]his might reflect increasing skill or possibly selection bias inasmuch as innately successful authors are more likely to survive" (Mela et al., 2013, p. 15). Those with multiple publications rarely get stuck at any particular level. For instance, 61% of scholars with at least two papers have three or more, a percentage that increases with three or more papers. A school hiring a currently active star researcher may be reasonably hopeful that the scholar's past publication success will recur. Unfortunately, the first publication rarely opens the floodgates, as 60% of scholars publishing in JCR or JCP have only one article (Mela et al., (2013) present a similar statistic (60%), as do Eaton et al., (1999) (63%)).

To give scholars grounds for optimism, note that our data is right censored; the second publication may yet arrive. The growth in consumer research means new scholars are relatively common in the data (e.g., JCR had 24 articles in 1974, but 90 in 2014; similarly, JCP started with 19 articles in 1992, but published 53 in 2014). Those who have published more than once have a median first publication date of 1997, but for scholars with only one paper, this median date is 2002. Furthermore, on average, the second publication took 4.3 years to arrive for those with two publications. Of the 1,434 scholars with a single publication, 367 (25.6%) have published in 2011 or more recently, suggesting they have not yet had time to gain a second publication. Many scholars with one paper are probably still actively pursuing more.

To summarize the consumer research community shows a similar publication skew to other research communities; a small number of very productive scholars compared to relatively large number of scholars with a small number of publications. We gave an indication of likely productivity, and noted increasing level of co-authorship.

R2: What does the community look like and is it even a meaningful construct?

The social network (Knoke & Yang, 2010) sheds light on why scholars co-author by allowing us to see who works with whom. In social network analysis, there are two primary types of data: nodes (vertices) and edges (connections). In our analysis, the nodes are the individual scholars/authors (e.g., Dilip Soman); accordingly, we have 2,404 nodes. Edges capture co-author relationships. We use undirected edges as we investigate mutual collaboration; mutual collaboration means your connection to me is the same as my connection to you.

Our definition of relationship, co-authorship, is relatively narrow. Matthew Thomson and Allison Johnson have worked together (for example, Thomson, Whelan, & Johnson, 2012) but without their publications we would never know that this married couple had met. We do not track co-authorship in other journals, mentorships, or friendships.

Some papers have only one author, generating no co-authorships, while other papers have as many as eight co-authors. As every co-author connects with every other, this creates $\frac{N!}{2!(N-2)!}$ co-authorships per paper where N is the number of co-authors on a paper, and ! is a factorial. Thus, an eight-person paper generates $\frac{8!}{2!\,6!}$ = 28 co-authorships. We examine relationships and therefore code multiple co-authorships as a single edge. More productive collaborations are shown by an edge's weight. For example, the Kardes-Cronley edge has an edge weight of 9, given their nine papers together (for example, Kardes, Cronley, Kellaris, & Posavac, 2004). In 0 we calculate total co-authorships and merge multiple co-authorships into a single edge to calculate the total number of edges: 3,880. The number of edges attached to each node is known as the scholar's degree, or degree centrality.

Table 2: Co-authorships and Edges

Panel A: Co-authorships given scholars credited on paper

Scholars	1	2	3	4	5	6	7	8
Co-authorships	0	1	3	6	10	15	21	28

Panel B: Papers by number of scholars credited on paper

Scholars	1	2	3	4	5	6	7	8	Total
JCP	144	325	210	61	11	5	0	1	757
JCR	416	935	492	72	19	5	1	1	1941
Total	**560**	**1260**	**702**	**133**	**30**	**10**	**1**	**2**	**2698**

Panel C: Total co-authorships (A*B)

Scholars	1	2	3	4	5	6	7	8	Total
JCP	0	325	630	366	110	75	0	28	1534
JCR	0	935	1476	432	190	75	21	28	3157

Total	**0**	**1260**	**2106**	**798**	**300**	**150**	**21**	**56**	**4691**

Panel D: Removing Multiple Co-Authorships to Create Edges

Edge Weight (# of Co-authorships Between Scholars)	Total Co-authorships	Total Edges
1	3301	3301
2	862	431
3	294	98
4	124	31
5	55	11
6	24	4
7	14	2
8	8	1
9	9	1
Grand total	**4691**	**3880**

We generated a representation of the entire social network using NodeXL (Hansen et al., 2010).[1] This is available on request, but the massive number of interconnections means it is not easily printable. However, we can summarize the graph in other ways; for example, paths between scholars. The path between Orie Kristel and Janet Schwarz is 2; they have not co-authored here but have co-authored with Peter McGraw, who connects them. The maximum geodesic distance is 15 (i.e., the longest direct path between two scholars is 15 connections). It is merely a fascinating oddity that the average geodesic distance, the degrees of separation, is six (6.006).

Graph density (Van Den Bulte & Wuyts, 2007) measures how likely each scholar is to work with each other scholar. Formally, it is the number of edges (3,880) divided by the total number of edges that there could potentially be (i.e. if everyone had published with everyone else). The maximum possible edges is the same formula as that for paper co-authorships $\frac{N!}{2!(N-2)!}$. At N=2,404, the maximum possible number of edges is 2,888,406. Thus, we have a graph density of 0.13%, (3,880/2,888,406). This lack of density is largely a consequence of our narrow definition of a relationship.

JCR and JCP have somewhat different remits, so does the same underlying consumer behavior community contribute to both journals? If the scholars publishing in each journal were unrelated, there would be no overlap and our dataset would have 2,881 unique individuals. If everyone in the smaller (JCP) group of authors has at least one article in JCR, the population would equal JCR's population, 1,844 individuals. Our analysis shows 2,404 unique individuals, midway between the hypothetic extremes. To avoid misinterpretation, we must clarify the reasons for the relatively modest overlap that we see, only 477 scholars (20%) have published in both journals. First, some scholars' publishing careers occurred before JCP's launch; they may have aimed to publish in JCP had it existed when they published. Second, our dataset is right censored at the end of 2014; active scholars who have published in only one journal may later publish in the other journal. Third, and most importantly, 1,434 scholars out of 2,404 have published only one article; clearly, these scholars have not published in both journals but this does not necessarily indicate a deliberate focus on a single journal.

We cannot predict future publications, but we can correct for authors with a single publication and authors active entirely before JCP's launch. We exclude from this analysis any scholar with only a single publication, which leaves 970. We then exclude those whose last publication was before JCP's 1992 launch (119), leaving 851 scholars with more than one publication and active in the "JCP era." Over half of these scholars (56%) have published in both journals. The majority of those able to publish multiple articles use both journals, which suggests a "consumer behavior" community exists, rather than the alternative conceptualization of separate JCP and JCR communities. We regressed the proportion of those at a given publication level who had published in only a single journal (either JCP or JCR) on number of publications. Those with more publications were less likely to have published only in one venue (β=-.016, p<.001). This isn't too surprising, those with more publications have more opportunities to publish in

[1] We recommend NodeXL, an easy-to-use Excel-based social network analysis tool, for the classroom too.

different venues, but it suggests those who can target both journals do so.

When we mapped the entire social network we saw that the maximum number of connected components is 1,734 connected nodes. (This is the total number of scholars who can be connected together without breaks). This means 72% of scholars are part of a connected whole, further supporting the idea of a connected community. That nearly three-quarters of scholars connect to the main group is especially remarkable, given that most only publish one paper. In total there are 315 groups; the single massive group of 1,734 scholars, and 314 very small groups. One-hundred and thirty scholars have their own group, never having co-authored.

Overall we noted that the community does seem to be a meaningful construct. Despite the majority of scholars having a modest level of publications in our dataset most can be linked up to each other through mutual co-authorship.

R3: What are the characteristics of successful scholars?

To analyze whether scholars who publish more differ in some other characteristics we classify some as highly productive. These researchers who publish five or more articles in our dataset. We choose this as the cut off because the mean publication rate in our dataset is 2.48 and the standard deviation 3.19. More than one standard deviation above average is between five and six publications which we round down to five.

These scholars are impressive, but we make no claim that they are the best consumer behavior scholars, given that a) five is an arbitrary cutoff, b) scholars publish in journals that we do not record, and c) successful careers are more than just a number count. Furthermore, it takes time to publish, meaning newer scholars are under-represented. Only four scholars whose first JCR/JCP article was 2010 or later are highly productive: Jesper Nielsen (Ph.D. UNC Chapel Hill, 2003), Clair Tsai (Ph.D. Chicago, 2007), Brent McFerran (Ph.D. UBC, 2009), and Theodore Noseworthy (Ph.D. Ivey, 2012).

Highly productive scholars comprise 13.1% (316/2404) of the population, but gained 47.4% of the author credits (2,818/5,951; the publications of scholars with 5+ publications in 0B divided by total publications). Highly productive scholars' JCP focus is similar to full population. Of all author credits, 29.6% were for JCP publications (1,761/5,951), compared to 28.3% for highly productive scholars (798/2818). Note that highly productive scholars start their careers before (average 1994) less productive scholars (average 1998) which matters as JCP was launched after JCR. We regressed JCP focus on a dummy variable, scholar highly productive =1, and the year of the scholar's first paper. Year of first paper was significant (β=.013, p<.001), starting a career later means greater JCP focus, but the highly productive scholar dummy was not significant (β=.018, p=.44). This suggests that highly productive scholars are prolific community members—not a separate community with unique publication habits.

Published papers are an individual characteristic because one can publish alone. Co-authorship metrics are different in that a relationship must occur for them to exist. We calculate each scholar's degree centrality, the number of his or her co-authors. Degree centrality is a function of a scholar's productivity, but also his or her co-authors per paper, and the variety of co-authors used. 0 shows the scholars with the highest degree centrality. Frank Kardes leads this list.

Table 3: Top Scholars by Degree and Betweenness Centrality

Scholar	Degree Centrality	Scholar	Betweenness Centrality
Frank Kardes	30	Baba Shiv	121,257
John Lynch	28	Aradhna Krishna	112,977
Vicki Morwitz	28	Gavan Fitzsimons	106,556
Baba Shiv	27	John Lynch	105,460
Gavan Fitzsimons	27	William Bearden	105,157
Darren Dahl	27	Joseph Alba	102,141
Chris Janiszewski	27	James Bettman	100,160
Kathleen Vohs	26	Vicki Morwitz	97,588
William Bearden	25	Robert Wyer	90,580
James Bettman	24	Frank Kardes	88,233
Robert Wyer	24		
Norbert Schwarz	24		

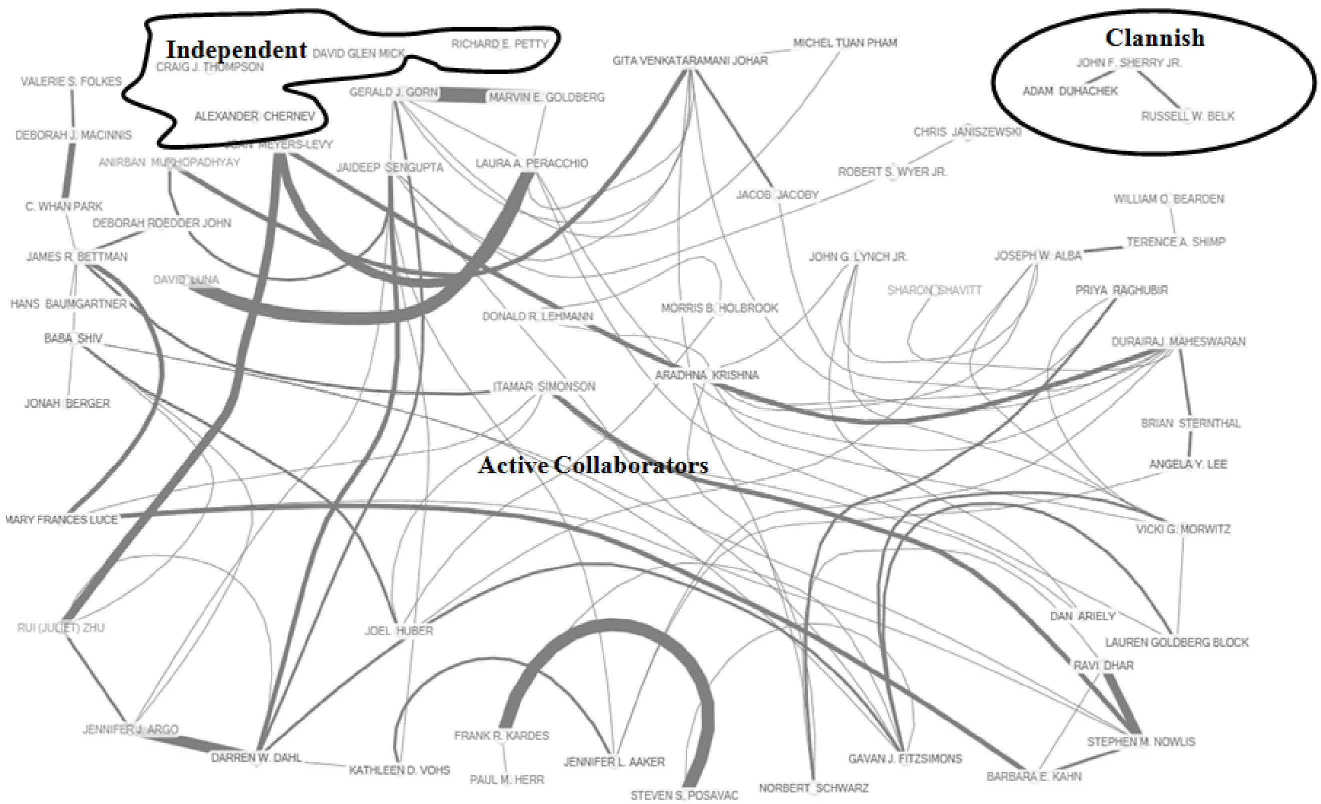
The same table shows *betweenness centrality*. Scholars with high betweenness centrality link groups. This metric is calculated as the number of the shortest paths between two scholars that go through this scholar. So the betweenness centrality of scholar v is:

$$Betweenness\ Centrality\ (v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Where σ_{st} is the total number of shortest paths from scholar *s* to *t*, and $\sigma_{st}(v)$ the number of these paths passing through v. Baba Shiv has the highest betweenness centrality.

We examine the connections among a group of what we call "hyper-productive researchers"—those who have published 12 or more papers. Limiting the sample this way allows us to visualize the social network (see 0). Further, focusing on these researchers allows us to consider scholars who, presumably, are successful enough that they have their pick of co-authors. The density of the "hyper-productive scholars only" network is high at 5.4%. They co-author extensively; one in 20 collaborations that could be made have actually been made. In this (subset of the entire) network, Jaideep Sengupta has the highest degree (9) and Baba Shiv the highest betweenness centrality (394).

Figure 3: Network of Hyper-Productive Scholars



Figures 3 and 4 created in NodeXL, Line Width = # of Joint Papers

We have invented three groups to classify the hyper-productive scholars:

The first group are *independent* —they do not work with other hyper-productive scholars. There are only four of these scholars. Note that these independently minded scholars have co-authored but, by definition, they just have not worked with colleagues who have also published 12 or more papers.

Another classification relates to the idea of an invisible college. This captures those who form focused groups. Let us call scholars in a discrete group *clannish*. The figure shows one such group, of only three scholars, connected to consumer culture research.

The final category is for hyper-productive scholars who are part of a group collaborating together. These hyper-productive scholars connect with other hyper-productive scholars who are all connected together; let us call them *active collaborators*. Here we include anyone who is part of the massive group of 51 connected scholars. The maximum distance between two scholars in this group is 9 (average distance 3.52).

The graph is messy because most scholars collaborate with a diverse range of others, who in turn collaborate widely. A separate analysis, not shown, highlighted that scholars beginning their careers more recently work together, but they also work with scholars whose careers started earlier, demonstrating inter-generational collaboration.

The network map shows that it is rare for any partnership to encompass the majority of a scholar's papers. This supplies some evidence against the gift authorship hypothesis (Henriksen, 2015). Hyper-productive scholars do not seem to work in small teams who credit each other simply to increase their publication numbers. Instead, we posit that the skills of the hyper-productive are valued by other hyper-productive scholars, who therefore collaborate on specific projects. Active collaboration also fits the idea of single community; these scholars have similar enough perspectives to work together.

Successful scholars provide a pivotal connecting role. Indeed, the clear majority of those scholars with

12 or more publications connect up with each through co-authorship.

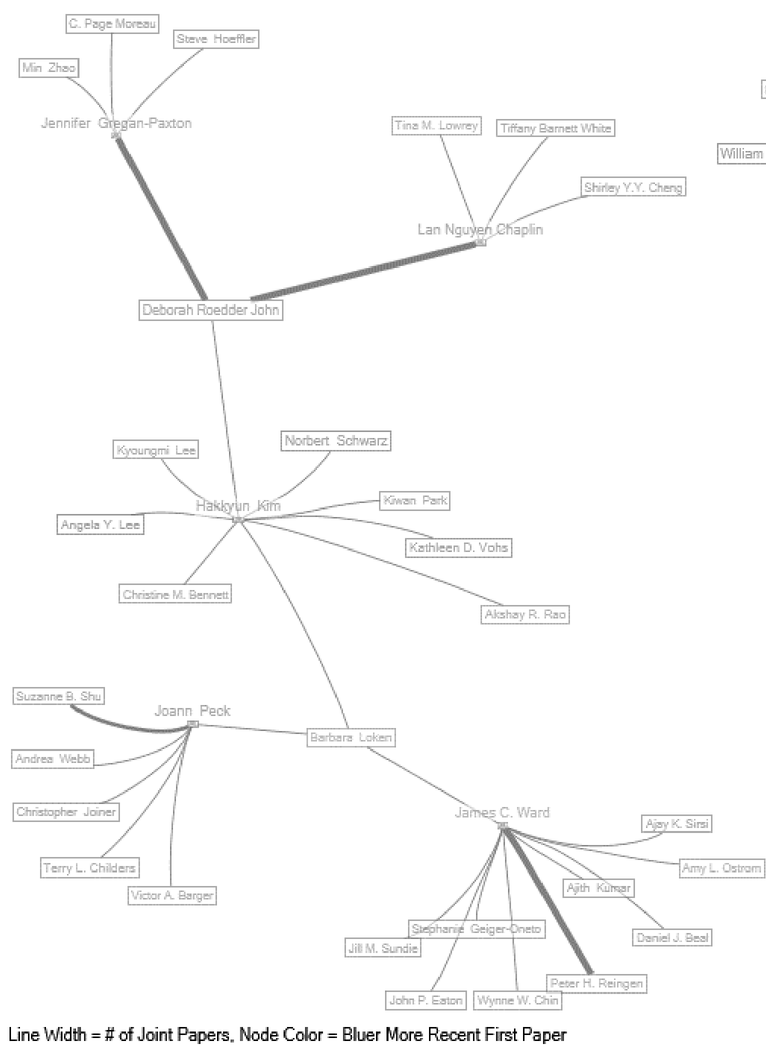
R4: Can we see schools as sources of connections?

Looking at the data by school is especially helpful for highlighting connections based upon training. Advisors and their students often co-author together. Indeed, the mutual interdependence of advisors and students (Schroeder et al., 1995) sets up something akin to a battle of the sexes (Bendle & Vandenbosch, 2014); these two groups need each other but their interests are not perfectly aligned, and mutual failure to compromise hurts everyone involved. Unfortunately, the nature of our data means that we can only really speak to successful relationships (at least in terms of productivity).

We recorded the schools where all highly productive (5+ papers) scholars trained, and can map any school's social network. We chose Minnesota as our example because the network fits well on a page but is large enough to be interesting. It has eight highly productive alumni (the names enclosed by a box in the figure). Including their co-authors, this gives a 76-scholar network (see 0). Note that we show all the co-authors of the eight highly productive alumni, but not the co-authors of their co-authors. This figure helps show how Minnesota is connected to productive scholars, such as Jennifer Argo and Darren Dahl, who never trained at the school.

This graph has a high density of 2.5%; in other words, one in 40 connections that could be made are made. Within the largest group the maximum distance between scholars is 6, and the average distance is 2.85.

Figure 4: Minnesota Highly Productive Alumni Network



The Minnesota graph's clear groupings can be partially explained by mentor relationships. The largest group (34 scholars) has two students of Deborah Roedder John (Lan Nguyen Chaplin and Jennifer Gregan-Paxton) and one of Barbara Loken (Hakkyun Kim). Hakkyun Kim has the highest betweenness centrality (356) because he links Barbara Loken and Deborah Roedder John. A second large group (24 scholars) has Russell Belk as the hub (and Belk has the highest degree centrality, 23). This group includes a number of his students (e.g., Thuc-Doan Nguyen and Rohit Varman). A final group (18 scholars) contains Rui (Juliet) Zhu's extraordinarily productive (notice the thick line) collaboration with Joan Meyers Levy, her advisor.

We visualized how schools link up scholars. Schools provide much more than a technical training or even co-authorship connections. In a well-connected community, like the consumer research community, training a PhD student allows the school an indirect relationship with productive scholars who never trained there.

DISCUSSION AND CONCLUSION

We used publically accessible data to analyze co-authorship among a set of consumer behavior researchers. Yet despite the large amount of data used, the picture remains partial and limited. Even using two FT45 journals, we still only focus on a subset of a scholar's co-authorships, and miss other ways that scholars contribute.

Our findings are consistent with those in other marketing and related journals in that we confirmed that there are very few highly productive scholars compared to those with a more modest publication level (Eaton, Ward, Kumar, & Reingen, 1999; Morlacchi, Wilkinson, & Young, 2005). The rising levels of co-authorship suggest that these results may generalize more widely. Further research is needed but is becoming more feasible. Computing power is cheap and social network analysis packages are available for popular software as R and Mathematica. The data needed to perform such analysis can be relatively easy to acquire from Scopus or Web of Science, and tools such as Publish or Perish (Harzing, 2007) make analyzing academic databases easier.

Our data description provides evidence for academic administrators as to the expected productivity of scholars. In general, publishing one paper (in these journals at least) is not solid evidence that there will be other publications, but those who publish multiple papers seem very likely to produce more. For example, in our dataset of those who were able to publish 3 or more papers 72% had achieved at least four papers. Our data also helps administrators to benchmark their school's performance (Elbeck & Schee, 2014; Soutar et al., 2015).

Emerging scholars and students may want to learn from the highly productive. Our results suggest that highly productive scholars are not part of an elite discrete network, but instead they connect to the main community. Neither are they unique in their focus on JCR over JCP, or vice versa. There does not seem to be a magic formula for success: highly productive scholars are similar to other scholars—they just publish more.

We created a social network for consumer behavior scholars and detailed the vital links. We mapped an illustrative network from a single school, which highlighted the role of mentors in the network. Focusing on the subset of hyper-productive scholars, we show that they are active collaborators; they work together for a paper or two but do not generally form exclusive clans with impenetrable boundaries. The theoretical take-away is that hyper-productive scholars are not as constrained by silos as one might hypothesize.

Despite these two journals' distinct foci they cater to many of the same authors. This is largely positive for consumer behavior scholars – many of them seem comfortable with both journals which gives them two possible FT45 venues to publish their work in.

Administrators benefit from a clearer knowledge of the consumer behavior community. One thing that might not be readily apparent is that star researchers bring more than just a large number of publications. They are natural links to other star researchers at other schools. One can see the positive side of social networks, despite any individual school only having a modest number of researchers (and an even smaller number of stars) the school is likely to be very effectively linked into the research community. Indeed social networks can be very positive; they allow for the transmission of best practice, new ideas, and allow for scholars to mutually influence each other. There is a downside however of interconnectedness which becomes obvious when one considers that a major use of social network analysis is to understand the spread of disease (Christakis & Fowler, 2011). Not only do good ideas and habits flow along social networks but so do bad habits and unhelpful ideas. The tight connections between so many consumer researchers means we should be especially vigilant to combat the transmission of habits that undermine the integrity of academic publishing. One example of which may be the problem of p-hacking, (Simmons, Nelson and Siminsohn, 2011) – bad habits associated with potentially motivated analytical techniques leading researchers to "find" the interesting results that they seek with a greater than expected probability.

Our work helps researchers to better understand consumer behavior scholarship through analyzing co-authorship in a subset of the field's journals. We also demonstrate the power of social network analysis in facilitating our understanding of the academic community

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