Scientific Collaboration and Co-authorship Patterns in Knowledge Networks: Dynamics and Trends in Behavioural Economics

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Abstract

This paper uses Social Network Analysis to investigate academic co-authorship networks. Focusing on the small and relatively new academic field of behavioural economics, I investigate whether scientific collaboration and co-authorship networks in this field exhibit the characteristics of social networks in general, and "small world" networks in particular. Moreover, I compare behavioural economics and its co-authorship networks against other more established academic fields such as mathematics and physics. Thereafter, I assess the extent to which the degree of professional success of individual authors within the network is related to indicators of their positioning within the network. I conclude by suggesting practical ways to deploy my findings, as well as future research directions.

Introduction

Collaborative research has gradually become the norm rather than exception for contemporary scientific advancement (Wuchty et al. 2007). One prevalent avenue of collaborative research lies in co-authorship relations, where two or more individual scholars or institutions jointly contribute to knowledge production via academic publication (Reagans 2003, Newman 2004). These knowledge-based partnerships are thus co-authorship networks. When taking a stratospheric view of co-authorship networks, these networks depict characteristics of the academic community alongside the organisational structure of knowledge production.

Why might we be interested in these co-authorship networks? In an ideal context, co-authorship based research can reap positive knowledge externalities, since scholars share ‘intimate technical knowledge and pool specialist expertise’ together (Goyal, 2003). Additionally, scholars in different disciplines may serendipitously gain access to other researchers and ideas, whether through discussion of developments in the field or even collaborating with a collaborator’s collaborators (Fafchamps 2006). These may precipitate new academic research pathways and instigate further research domains (Jaffe, 2000; Newman, 2003).

However, the above are but aspirations rather than actualities. The extent of these benefits are very much dependent on the specific properties of the co-authorship relations. After all, not all collaborative relationships are beneficial. Consider this scenario. Suppose co-authorship networks reveal that researchers cluster together with similarly affiliated researchers exclusively. This may constitute a cohesive academic core at the expense of integrating fresh ideas and new researchers into their own circles. At its worst, we may find a fragmented academic community characterised by different schools attempting to self-legitimise and anoint their knowledge paradigms as orthodoxy, as in the case of theoretical physics (Smolin 2006).

Additionally, not all researchers enter into co-authorship relations equally. For example, young researchers often partner with a senior researcher such as a supervisor or an established expert in order to gain research experience. It is reasonable to assume that the senior collaborator chooses his/her younger colleagues carefully, for reasons of reputation. As such, the specific identities within one’s co-authorship network become of interest as proxies to measure the standing and perceived potential of individual researchers. This may lead to asymmetric relationships, where more senior researchers who experience ‘post-tenure fatigue’ may rely on junior researchers to boost their own publication record while contributing minimally to the final work (Paris 2006). The implications of these power dynamics can exert consequences for the brokerage of academic information, faculty decisions in hiring and the allocation of research funding.

Using Social Network Analysis (SNA) to study these problems, the present studies analyses the co-authorship patterns within behaviour economics. This contributes to the existing literature in 2 ways. Firstly, while SNA has been applied to the analysis of knowledge networks in mathematics (Grossman, 2002), physics, computer science (Newman, 2001) and economics (Goyal, 2003), behavioural economics has not been analysed as a knowledge domain. As a relatively young academic field, there are grounds to suspect it might differ from other knowledge networks. Secondly, being a field that is intentionally multi-disciplinary, this may also be a source of variegated scientific collaboration and co-authorship patterns as compared to other knowledge networks.

Social Network Analysis and Scientific Collaboration

The intuition behind social network analysis and scientific collaboration shares theoretical affinities with sociological studies of scientific collaboration. For example, Randall Collins in the *Sociology of Philosophies* traces the growth of intellectual schools and lineage such as that of classical Greek thought from Socrates to Plato to Aristotle and beyond (Collins, 2009). Borrowing methodological tools from other disciplines such as informetrics and mathematics to describe these relationships, sociologists such as Mark Granovetter already deployed basic techniques to formalise studies of 'weak ties'. Using network diagrams, he studies connections that require little emotional or physical attachment i.e. weak ties, but greatly facilitate communication since parties do not mutually conflict when holding contrarian views given the low frequency of contact. The corollary is that fresh views may be obtained when both parties do end up during an occasional meeting given the non-synchronicity of their ideas.

The partnership between social network analysis and co-authorship networks has been a fruitful one, bringing research effort on par with interest in citational networks. Major problems include how to quantify the optimal advantage that a co-authorship network potentially possess, as well as developing techniques required for analysing longitudinal network data and actor attributes.

More importantly, these have resulted in a number of important applications. One such analysis performed on Brazilian topical diseases researchers find that some research on some diseases were emphasised to the detriment of others, often with a high correlation with research funding. Additionally, some components such as the medical and biological aspects received more attention than epidemiological concerns such as disease vectors and control activities. Moreover, co-authorship networks revealed that researchers in similar domains largely confined themselves to geographically convenient co-authors, with additional studies suggesting that there was a lack of coordination and communication that led to unnecessary research overlap and thus affecting overall productivity. One can think of parallel situations where such analysis would be welcomed, such as research efforts following the recent Ebola epidemics in Western Africa.

Co-authorship networks and the 'Small World' Phenomenon

Small world networks were first made famous by Milgram's 'six degrees of separation' (Milgram, 1967). In that experiment, Milgram demonstrated that individuals were connected within a 'tightly knitted social fabric' (Milgram, 1967) since the experiment participants were linked to each other by at most five intermediaries. Formally, small world networks are defined as 'large-*n* networks that exhibit (i) characteristic path lengths close to that of a random network[8] ($L_{actual} \approx L_{random}$) and (2) clustering coefficients greater than its random equivalent ($C_{actual} > C_{random}$)' (Watts, 1999).

How are 'small world networks' important for co-authorship networks? Firstly, homophily, or association by similarity (McPherson 2001), govern human interaction. Individuals are more predisposed to behaviours as embodied by the adage 'birds of a feather flock together'. Secondly, there are advantages in creating weak ties (Gallos 2012). Individuals may want to access others that are not within their dominant clusters in order to gain access to individuals that are

[8] A random network is generated by taking the equivalent number of nodes in the actual network and randomly allocating connections (vertices) between them.

otherwise far away from self and immediate neighbourhood. Similarly, the ability to incorporate new ideas from different scholars also influences new co-authorship arrangements beyond one's already existing co-authors. Small world configurations allow researchers to be 'nearer' to each other, and hence facilitate exchange of ideas, contacts and even collaboration opportunities. Having said this, I cannot stress further that that small world networks are *models*, rather than a social facts and hence the presence of small world features should not by default be indicative of a healthy state of knowledge production.

The *characteristic path length* refers to the average shortest distance (geodesic distance) between all pairs of nodes in the network. In co-authorship pattern terms, *path length* between two nodes X and Z indicates the distance between author X and author Z, whether through immediate collaboration or through intermediary author(s) who have collaborated with both X and Z. For example, in Figure 1, A is connected to E through B, G and F, hence the path length here is 4. The characteristic path length is the average of all such shortest path lengths.

Clustering coefficients refer to 'the probability that a connected triple of nodes is actually a triangle' (Strogatz, 2001). In co-authorship pattern terms, this refers to the probability that 2 authors working with a mutual collaborator are themselves collaborators.

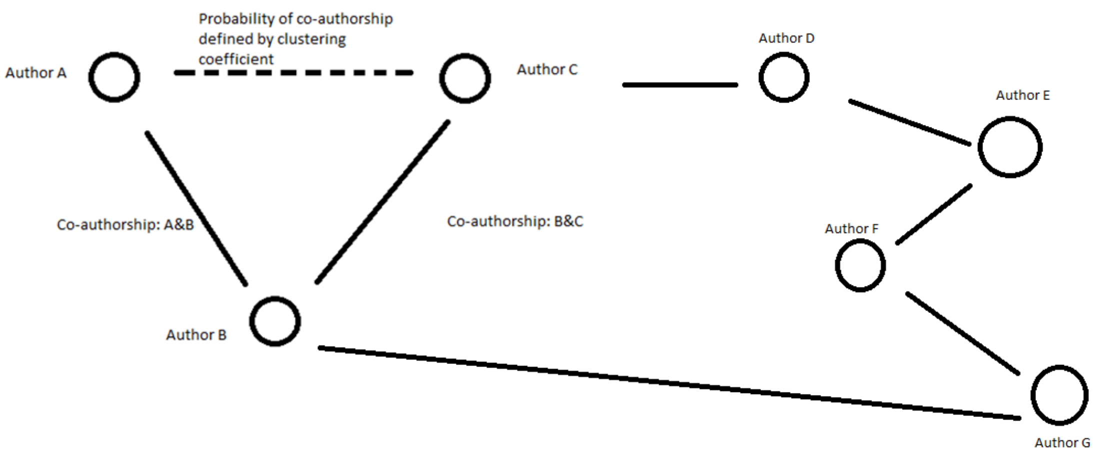


Figure 1: Visual representation of networks, characteristic path lengths and clustering coefficients

Using a 'small-world' model definition, ascertaining if a knowledge network is small-world is achieved through comparing the actual characteristic path length and clustering coefficient with a randomly generated network with an equal number of constituents. The formulations for obtaining the random equivalents are as follow:

$$L_{random} \sim \frac{\ln(n)}{\ln(k)}, \qquad C_{random} \sim \frac{k}{n}.$$

Equation 1 Equation 2

Despite differences in social dynamics and environments, networks such as the World Wide Web and Facebook relations have evolved over time to fulfill 'small world network' conditions. Knowledge networks over various academic domains also demonstrate such similar empirical affinities.

Strategic Individual Positioning within Knowledge Networks

Within SNA, centrality indices are concerned with properties about how nodes are connected with each other. These properties have strategic significance, since they can determine the importance of a node within a network. In other words, we are asking questions regarding who is important, why is he/she important, and the usefulness or potential abuse of one's importance.

Degree centrality refers to the number of edges connected to each node (Freeman 1978). The computation is as follows:

$$C_D(p_k) = \sum_{i=1}^{n} a(p_i, p_k)$$

$C_d(P_K)$ - degree centrality

N - number of nodes

$a(p_i , p_k)$= 1 if and only if nodes I and K are connected, otherwise $a(p_i , p_k)$=0

Betweenness centrality (Freeman 1978) refers to the number of times a particular node lies on the shortest path that links 2 other nodes together. The computation is as follows

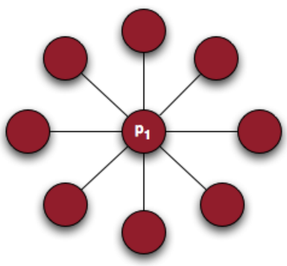
$$C_B(p_k) = \sum_{i<j}^{n} \frac{g_{ij}(p_k)}{g_{ij}}; i \neq j \neq k$$

$C_B(P_K)$ – Betweenness Centrality

N – Number of nodes

G_{ij} –geodesic distance (shortest path) linking p_i and p_j.

$G_{ij}(P_k)$ – geodesic distance (shortest path) linking p_i and p_j that contains p_k



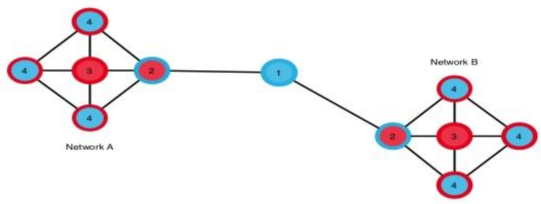


Fig.1 High Degree Centrality (Node P1) Fig.2 High Betweenness Centrality (Node 1)

Both centrality indices refer to different types of importance, and hence it is important to differentiate them. High levels of degree centrality indicate that authors are well connected within the network. The higher the degree centrality index for an author, the more collaborators he/she has worked with. A high betweenness centrality indicates that an author acts as the 'middleman' between other authors. The higher the betweenness centrality index for an author, the better he/she can act as a broker for information, or connecting disparate individuals and groups working in different clusters.

Existing co-authorship literature identifies betweenness centrality as a better indicator of power or influence (Krackhardt, 2010). Firstly, the centrality indices are not transitive between authors i.e. even if an individual has high degree centrality, he/she may still record a 0 for betweenness centrality. This implies that authors who broker information or contacts will necessarily be connected, but highly connected authors may not be able to broker information. Secondly, authors with high betweenness centrality connect disparate individuals or clusters to each other imply that they control information flows, and can potentially influence research direction and fashion. However, having a high degree centrality i.e. high connectivity is also intrinsically important, since direct transmission of ideas occur vis-à-vis collaboration.

Data and Methods

Data

Using primary data that was data-mined from a number of sources, I obtained 3 datasets:

1) Specialist behavioural economics journals (Main 3): Journal of Behavioural and Experimental economics, Journal of Economic Psychology, and Journal of Economic Behaviour and Organisation. This was obtained through Sciencedirect, which is provided by Elsevier.
2) A keyword search of 'behaviour', 'behavior', or 'economics' on the American Economic Association EconLit database, followed by refining the results using keywords such as 'psychological aspects, economic aspects, fairness, behaviour, psychology, socioeconomics, social psychology, economic factors, experimental economics, decision making, choice behaviour' (Berg and Gigerenzer 2010; Heap 2013).
3) Since Econlit only covers journals from the American Economic Association, I broadened my search to include the top 15 impact factor journals (Repec, 2013). A JSTOR search was conducted to capture relevant papers using the above procedure of a keyword search followed by a refinement of the results through a glossary of keywords.

Thereafter, I manually inspected entries in the dataset to prevent duplication arising from factors such as misspellings or different abbreviations due to the different bibliometric data sources. Using Bibtex to export and process the citation information, my final dataset comprised 10,240 authors, as obtained from 9,306 papers.

For the analysis of research performance, I chose two metrics. The first is a measure of citation counts. However, citation counts cannot be used on their own insofar as they are not normalised for the number of papers produced by each author. Moreover, citation counts do not differentiate between authors who maintain consistently high numbers of citations and authors who may produce one highly cited paper but fail to make an impact with other papers.

The second measure is an "H-index". A researcher is defined as having an H-index of *h* if '*h* of his papers have at least *h* citations and the other remaining papers have at most *h* citations each' (Hirsch, 2005). Arguably, this constitutes a more holistic metric to quantify research performance, and has been widely utilised in informetrics research (Tol 2008). H-index is also a good predictor of future achievement when compared with the total number of citations (Acuna et al, 2012).

I selected two such subsets. The first is a list containing the top 100 performers in terms of betweenness centrality. After removing repeated authors, I was left with 92 top researchers.

In addition, I created a parallel list of 92 authors taken from the full range of the dataset. I used a systematic sampling frame to do so, and took every 111th entry to create this list (10240/92 ≈ 111).

Findings

<u>Can the system of co-authorships in Behavioural Economics be considered as a "small world" network?</u>

In order to assess whether co-authorship networks in behavioural economics approximate to a "small world" network, clustering coefficients and path lengths were calculated over different time periods. Table 1 shows the results of this analysis.

Table 1: Chronological table depicting the evolution of Behavioural Economics.<u>1</u>

Year	Actual Clustering Coefficient	Random Clustering Coefficient	Average Characteristic Path Length	Random Network Shortest Distance	Diameter
Papers published up to and including 1990	0.718	0.0000397	1.92	7.8	6
Papers published up to and including 1995	0.772	0.0000266	2.27	8.6	9
Papers published up to and including 2000	0.781	0.0000526	2.6	9.7	9
Papers published up to and including 2005	0.773	0.0000295	6.73	16.5	21
Papers published up to and including 2010	0.773	0.0000211	9.78	17.8	30
Papers published up to and including 2013	0.779	0.0000977	8.85	17.4	27

In all 6 timeframes, the clustering coefficient ranges from $0.718<C<0.779$ This was significantly higher than the clustering coefficient generated from the random network simulation obtained by formula (2).

In all 6 timeframes, the average characteristic path length range from 1.92<Path length<8.85. This was significantly lower than the characteristic path length generated from the random network simulation obtained by formula (1).

Based on the definition set above, behavioural economics as a knowledge community can indeed be thought of as a 'small-world' network.

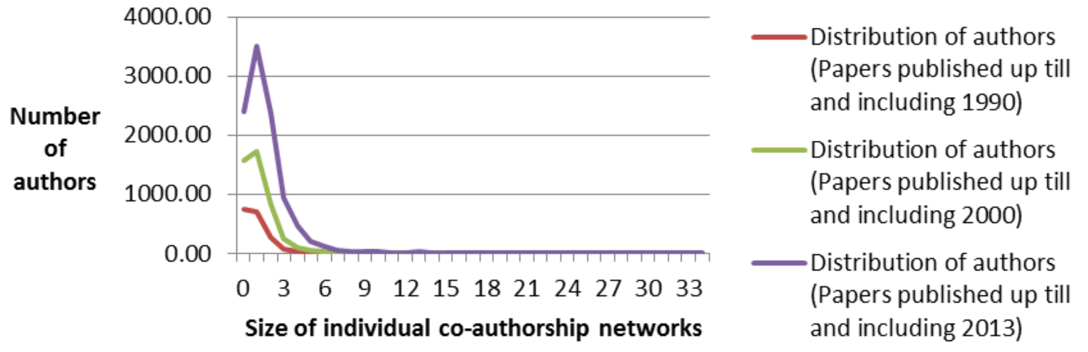
<u>What are the co-authorship patterns within Behavioural Economics?</u>

Figure 1 shows the distribution of the sizes of individual co-authorship networks over 3 time periods. The overlaps in the timeframes were necessary since there were incumbent authors in an earlier timeframe who may collaborate with a new entrant researcher from a later time frame.

Despite growths in the total research output in behavioural economics, co-authorship patterns remained stable through all 3 sampled timeframes. The majority of authors only collaborated with at most 1 other author. It is also an enduring phenomenon that the number of single authors remained persistently high. This trend was also evident when the average number of authors per paper was considered, with a mean of 2 authors per paper.

However, the maximum number of co-authors increased, from 12 co-authors in 1990 to 34 co-authors in 2013. Despite this, these researchers were in the minority.

Figure 1: Size of individual co-authorship network over 3 time periods



How do the characteristics of co-authorship networks in Behavioural Economics differ from other disciplines?

Table 2: Comparison of co-authorships in behavioural economics with other knowledge disciplines

	Total Authors	Clustering Coefficient	Largest Cluster	Largest Cluster as % of Total Population
Biomedical	1520251	0.066	1395693	92.6%
Physics	52909	0.43	44337	85.4%
Mathematics	192000	0.15	n.a	60%
Computer Science	11994	0.496	6396	57%
Economics	81217	0.157	33027	40%
Behavioural Economics*	4576	0.780	52	1.14%
Behavioural Economics**	10240	0.779	1086	10.6%

Notes: All other knowledge networks were obtained between and including 1990-1999.

* represents behavioural economics up till and including 2000.

** represents behavioural economics up till and including 2013.

With behavioural economics' (as of 2013) largest cluster at 10.6% of the local population, this is lower than the other academic fields. This indicates that the research network is segregated into smaller academic units, and individuals do not orbit about the same co-authors as frequently as other domains.

However, since the populations in each of the other disciplines are high, these results in behavioural economics also have to take into account the relatively small research network as compared to the others.

Are different positionings within the network associated with different degrees of success, and how do they differ?

1) Subsample of the top 92 betweenness centrality authors

A Kolmogorov-Smirnov test normality test showed that neither citation counts nor the H-index were normally distributed, with citation counts at $D(92) = 0.268$, $p<0.05$ and H-index at $D(92) = 0.142$, $p<0.05$. As such, the non-parametric one-tailed Spearman Rho rank correlation is appropriate.

There were significant positive correlations between *degree centrality* and both citation count and the H-index. For degree centrality and citation counts, $r=0.271$, $p=0.004$, $p<0.05$. For degree centrality and H-index, $r=0.274$, $p=0.004$, $p<0.05$

Betweenness centrality was positively correlated with the H-index in a significant manner. For betweenness centrality and H-index, $r=0.182$, $p=0.04$, $P<0.05$

The relationship between citation count and betweenness-centrality was insignificant ($r=0.168$, $p=0.55$, $p>0.05$).

2) Systematically Sampled subsample of authors

A Kolmogorov-Smirnov test normality test showed that both citation counts and H-index for the systematically sampled list were not normally distributed, with citation counts at $D(92) = 0.316$, $p=0.005$, $p<0.05$. and H-index at $D(92) = 0.113$, $p=0.01$, $p<0.05$. As before, the non-parametric one-tailed Spearman Rho rank correlation is appropriate.

Once again, *degree centrality* was significantly positively correlated with both citation counts and the H-index. For degree centrality and citation counts, r=0.245, p=0.009, p<0.05. For degree centrality and H-index, r=0.274, p=0.004, p<0.05.

As before, *betweenness centrality* was positively correlated with the citation count and H-index in a significant manner. For betweenness centrality and citation count, r=0.398, p=0.00042, p<0.05. For betweenness centrality and H-index, r=0.325, p=0.01, P<0.05.

For both groups, the results show that research performance is positively correlated with betweenness and degree centralities. However, there were differences between the two groups regarding which of the indices was the better predictor for research success. In the top betweenness centrality group, degree centrality was clearly the better predictor. In the systematically-sampled group, however, betwenness centrality was a better predictor of the H-index.

Discussion

The analysis in this paper has demonstrated that behavioural economics does constitute a small-world network, with actual shortest distances between nodes being much less than the random network simulation. This bodes well for the field insofar as access to different authors, and by extension different ideas are more accessible. Once again, I emphasise that these findings and the substantive interpretations that I offer are hypotheses that I invite others to affirm or challenge.

The benefits of positive knowledge externalities seem to be present present, and this benefits the research community as a whole. Taking a metaphor from the natural world, multiple connections between different cells or clusters further increase the organism's survival probability and its complexity (Barabasi 2002). A diversity of connections acts as a hedge to prevent any unit from being overly dependent on one particular node. In our context, if a researcher gets too dependent on one particular co-author, this may not be beneficial since a variety of reasons such as lack of inspiration, intellectual drought, or even death could deny the individual of a valuable working relationship if the said individual is too comfortable in this arrangement.

Additionally, the short average distance between researchers in behavioural economics than its randomised small work equivalent implies it is easier for two individuals working in related fields to meet and collaborate. However, the majority of authors in behavioural economics still maintain co-authorship patterns of having at most 1 other co-author. Moreover, despite behavioural economics being a small-world network, the largest cluster in behavioural economics remains smaller than that of other knowledge domains. Furthermore, the majority of authors in behavioural economics are detached from the overall community of researchers

What does these results imply? One possible explanation is that behavioural economics researchers, despite its inter-disciplinary origins, tend to hover around individuals within their subfields i.e. economists with economists. Another may pertain to institutional elitism, where authors primarily co-author together with individuals from similar type institutions. as compared to other domains (Vega, 2007). Nevertheless, it is possible to come up with more charitable interpretations. Perhaps the predominance of individual or bi-author papers suggest that behavioural economics is gradually being accepted into mainstream economics, where more researchers are willing to incorporate the tenets of behavioural economics into their own work in other areas. Also, the lack of developed clusters may simply allude to the peculiar nature of behavioural economics, where researchers focus on a wide range of discrete psychological and behavioural attributes and their specific economic implications as compared to 'big theory' construction. One similar epistemological parallel may be found between the qualitative differences between combinatorics and number theory.

With regards to centrality indices and research performance, the results were mixed. Degree centrality appears to be a better predictor than betweenness centrality for citation counts, as well as H-index for the top 92 betweenness centrality performers. This contradicts other results that show betweenness centrality as being more important for citation counts as well as h-indices (Abbasi 2009, 2010). Yet, betweeenness centrality was a much better predictor with the systematically sampled group. Explanations for both sets of results are possible. Research with those results was conducted in fields that are well defined, such as steel structures as well as computer science.

Interdisciplinary research such as behavioural economics can demonstrate different network dynamics. Despite this, the external validity of these results cannot be guaranteed, and a comparative of other interdisciplinary research fields in the social sciences will be useful, e.g. neuroscience.

Practical uses

Inevitably, the purportedly 'evidence-based' policy maker, or funding evaluator, may find the above results to be useful for decisional making regarding limited research funding or manpower deployment. A potential area to further augment research dynamics is with regards to the research within behavioural economics. In terms of capacity building, this can help justify the creation of more deliberate or intentional platforms such as a world congress of behavioural economics in order to boost more collaborative opportunities.

The evidence-based practitioner will also find the centrality indices to be of interest. Within an academic environment, this can be used for faculty recruitment, promotions and other performance related affairs. Research funds through foundations or governmental allocation also require selecting scholars who are not only individually capable, but also able to maximise research output, cost savings and resource utilisation (Jiang 2008). Also, where prospective post-graduate students or researchers choose institutions, supervisors or collaborators to approach, this information could also be useful under such circumstances.

Limitations and Future Research

There are a number of intuitive research directions that we can embark on where the above analysis left off. One interesting area would be to study other platforms that allowed co-authorship opportunities beyond the standard format of academic publication. One particular example is wiki-styled research vis-a-vis crowd-sourcing. The latter is embodied in mathematical research through Timothy Gower's Polymath Project, where problems are posed online and individual contributors can collectively discuss and tackle these problems. SNA can be deployed to investigate online wiki-styled research participants, and if those collaborations already exist on other platforms such as co-authorship configurations.

Having said that, there are a number of limitations with the data that impede an exploration into interesting questions of co-authorship dynamics. In my datasets, I did not differentiate between age, nationality, gender or institutional affiliations. This will be useful to as substratas to place researchers in and would have been useful to identify other types of dynamics such as gendered patterns of co-authorship, or institutional hierarchy for scientific-collaboration. However, the process of obtaining such data may be more challenging than what I have done in this report. More insights regarding external validity type questions about other knowledge networks can be addressed along these lines too.

Another possible area of study is the nature of asymmetric power dynamics between collaborators[9]. One proxy of such dynamics revolves around the order of authors on a paper. In some scientific fields with primary investigators, authors are arranged by descending order of contribution with the last author usually the one with funding. This may invoke problems of subtle academic exploitation. However, the lack of standardisation across different journals complicates an already sensitive topic of relative contribution, especially if using data over a long period of time where journal policies may differ under different editors. However, a similar if not equally interesting question may be asked: How can we capture the influence that one researcher has on another in terms of topics and ideas and vice-versa? More concretely, suppose a psychologist and an economist were to enter a collaborative partnership, each would bring about different expertise into the project that the other by definition cannot individually compensate for. This problem has been studied using machine learning and Bayesian approaches, though methodologically it complicates the substantive interpretation component.

Evidently, where social network analysis allowed methodological access to co-authorship trends at an aggregate level, it lacked the in-depth explanations that interviews or ethnographic analysis would have provided. Nevertheless, these are tradeoffs only when upholding unproductive schisms between qualitative and quantitative research that a mixed method approach can otherwise bridge. SNA should be a

[9] I thank an anonymous reviewer for highlighting this point.

welcomed approach into the social sciences, albeit in a constructively critical manner.

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