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Cross-Affiliation Collaboration and Power Laws for Research Output of Institutions: Evidence from Top Journals in Financial Economics*

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Abstract

Cross-affiliation emerges as a new and fast-developing means to promote collaboration in financial research. We find that the average number of affiliations reported per author in the top-three finance journals increases steadily from 1.1 to 1.3 from 1995 to 2016. Scale-free power laws characterize the resulting highly-skewed distributions of top finance journal publications of worldwide institutions. We propose an explanation of the scale-invariance, based on a network model featuring nonlinear growth and linear preferential attachment. We show that preferential allocation of publications through success-breeds-success engenders disparity in institutions' research output, while acceleration in the growth of collaboration reduces the dispersion.

JEL Classifications: D85, G00
Keywords: Research collaboration, cross-affiliation, power laws, accelerated network, preferential attachment

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1. Introduction

Recent decades have witnessed the fast growth of research collaboration in social sciences (see, e.g., Moody, 2004; Van Noorden, 2015; Buyalskaya, Gallo, and Camerer, 2019). In Economics, in particular, Goyal, van der Leij, and Moraga-González (2006) pioneer coauthor networks of economists and demonstrate that the social distance between economists who publish in journals declines significantly during 1970-2000. The three coauthor networks of economists, one for each decade, display small-world properties of Watts (1999). In additional to formal collaboration through coauthorship, Laband and Tollison (2000) point out that informal intellectual collaboration through commenting on a paper or discussing it at workshops, seminars, or conferences is also commonplace in Economics and to a lager extent than that in Biology. Both formal and informal collaboration have positive effects on research productivity[1] (see, e.g., Ductor et al., 2014; Ductor, 2015; Rose and Georg, 2019).

This paper investigates a new means to further promote collaboration, that is, cross-affiliation in which researchers expand their scope of collaboration by affiliating with multiple institutions. Here, we focus on the widely-acknowledged top-three general interest journals in Financial Economics, namely, the *Journal of Finance* (*JF*, founded in 1946), the *Journal of Financial Economics* (*JFE*, founded in 1974), and the *Review of Financial Studies* (*RFS*, founded in 1986), which serve as clear exemplifications. We study top journals for two reasons. On one hand, top journal publications have a powerful influence on the impact of the underlying research. They also carry vast weight in the career paths of academic researchers, the recruitment decisions of research institutions, and the allocation of research funding. Hence we may intend first to obtain results regarding top journals. On the other hand, space in top journals is

[1]For general discussions on the benefits of collaboration, see, e.g., Beaver (2001).

limited. Competencies in assembling research teams, communicating with peer experts, and acquiring research resources (e.g., data accesses, hardware and software, funding, visibility, and credibility) across institutions play a more and more important role in top journal publications. Intense competition[2] forces researchers to develop new forms of collaboration. And top journals constitute natural sites where these new forms of collaboration emerge.

We hand-collect the author and affiliation information for all articles published in the top finance journals. Figure 1 presents the patterns of collaboration in these journals during 1980-2016.[3] Panel A shows the average number of coauthors by aggregating the three journals. Coauthorship displays steady, approximately linear growth observed earlier in other fields, such as Economics (Card and DellaVigna, 2013) and Neuroscience (Barabási et al., 2002). Panel B shows the new form of collaboration through cross-affiliation. We plot here the average number of institutional affiliations reported per author by aggregating the three journals.[4] The number lingers at a low level before 1995 but starts to ramp up thereafter. In twenty-two years, the average number of institutions per author climbs from 1.1 to 1.3. Put differently, on average, 1 out of 9 authors is affiliated with multiple institutions before 1995, while the ratio increases to 1 out of 3 at 2016. Panel C shows the average number of institutions per author separately for each journal. The same trend is prevalent across all three.

The new form of collaboration through cross-affiliation imparts fresh insights into the growth of research output of institutions gauged by their top journal publications.

[2]For instance, Card and DellaVigna (2013) show that the total number of articles published by the top-five economics journals remains relatively stable accompanying the outburst of submissions in recent years. As a result, the acceptance ratios have fallen off dramatically. Similar situations apply to the top finance journals.

[3]Prior to 1980, an author usually reports a single affiliation. Therefore, this earlier period is less informative for our study of cross-affiliation and omitted for simplicity.

[4]Li et al. (2018) study collaboration across institutions in materials science. They do not characterize cross-affiliation but focus instead on the percentage of multi-institutional publications, which starts to grow around 2014.

In this study, we find that research institutions self-organize into a scale-free state and their top finance journal publications are characterized by power laws in the upper tail. The upper tail retains 6.0% of the totally 828 institutions at the end of 2016, while these most prolific institutions produce 61.3% of the totally 13548 top journal publications. The upper tail distribution is highly-skewed: the mean number of publications is 166 while the most productive institution, NBER (National Bureau of Economic Research), contributes 1105 publications. The power laws govern institutions of diverse nature and scattered across geographic regions and time of establishment, indicating that these specific traits of institutions may be of less importance in driving the dynamics of their research output. The power laws are robust when considered separately for each of the last six years during our sample period. This result enables us to make further inference on the network since it seems to have reached a steady scale-free state. The power laws are also robust when considered separately for each of the three journals. This result reassures us that the scale-invariance is not caused by some journal-specific policies.

Our results provide an important regularity for theories of research output growth, which target the empirical power laws documented here. We propose a model of collaboration network that explains the scale invariance, based on further examinations into the structural reasons for the emergence of the scale-free properties. Specifically, a research institution enters the network as a node when it first publishes on a top finance journal and its degree henceforth equals its total number of publications. Two institutions are linked if they are affiliated to by at least one author of an article published in a top finance journal.[5] The deep collaboration in financial research is revealed by a giant component of the network, which consists of 99.5% of all the institutions at the end of 2016.[6] The dynamics of the network system are driven by nonlinear growth through

[5]To fully account for the complexity of the collaboration patterns, we admit multi-links for repeated collaboration between two institutions and self-loops for articles reporting a single affiliation.

[6]Fatt, Ujum, and Ratnavelu (2010) document that the largest component covers 58% of the nodes

enlarging coauthorship and cross-affiliation, as well as linear preferential attachment by incrementing total publications of institutions at a rate proportional to their current counts. The two mechanisms are generic, regardless of the types (universities, research centers, banks, etc.) and other characteristics (location and time of establishment) of the institutions. We consider three channels to allocate new degrees/top journal publications: i) publications brought about by new nodes; ii) publications allocated randomly to existing nodes; and iii) publications allocated preferentially to existing nodes. The model predicts a power law for the stationary degree distribution in the upper tail. Furthermore, the power exponent is inversely related to the proportion of preferential allocation. Using the estimated power law exponents, we compute that 87.0% of the total publications originate from success-breeds-success,[7] which engenders the high skewness in the distributions of the institutions' research output. On the contrary, the model also predicts that accelerated growth of collaboration increases the power exponent, and hence works to restore the homogeneity of the institutions.

Power laws are an important empirical regularity for a wide spectrum of natural and social phenomena (Dorogovtsev and Mendes, 2003; Jackson, 2008). Beginning with Pareto (1896), well-documented power laws in Economics and Finance include individual wealth/income, international trade, city size, stock-market activity, firm size, CEO compensation, and supply of regulations (see Gabaix, 2009, and the references therein). In academia, the number of papers written by individual scientists, the number of coauthors of mathematicians, and the number of citations of papers also follow power laws (Newman, 2003). This paper provides evidence from Finance Economics that

in the coauthor network of *JF* between 1980 and 2009. Hence we may expect the giant component of the collaboration network of institutions to be extraordinarily large since each institution commonly accommodates a number of economists.

[7]Bol et al. (2018) document the success-breeds-success effect in the allocation of science funding in the Innovation Research Incentives Scheme, a primary funding source for young Dutch scientists, in the Netherlands.

research output of institutions obeys power laws.

The literature on studies of research collaboration through the lens of social networks starts with Newman (2001b,c,d).[8] Barabási et al. (2002) extend Newman's analyses of static networks and examine the dynamics and evolution of coauthor networks. Goyal, van der Leij, and Moraga-González (2006) treat Economics as a unified discipline and investigate coauthor networks of all journal articles included in the EconLit database. Fafchamps, van der Leij, and Goyal (2010) find that the distance between two authors in the network is negatively related with the probability that they will form research teams in the future. van der Leij and Goyal (2011) examines the strength of strong ties in the network. Ductor et al. (2014) and Ductor (2015) find that coauthorship increases research productivity. Several studies investigate subfields of Economics including Evolutionary Economics (Dolfsma and Leydesdorff, 2010), Econometrics (Andrikopoulos, Samitas, and Kostaris, 2016), Population Economics (Brown and Zimmermann, 2017), and Financial Economics. For coauthor networks[9] in Financial Economics, Fatt, Ujum, and Ratnavelu (2010) explore coauthorship in *JF*. Andrikopoulosa and Trichas (2018) study coauthorship in the Journal of Corporate Finance (*JCF*), which is the oldest academic journal specializing in corporate finance research. Exceptionally, the two authors give an example of the ego-network of the City University of Hong Kong, although they do not further examine the collaboration network of institutional affiliations of financial economists who publish in *JCF*. Li et al. (2018) find scale-free features in

[8]Coauthorship as a measure of research collaboration dates back to de Solla Price and Beaver (1966). Hodgson and Rothman (1999) define the concentration of publications in economics (including finance) as institutional oligopoly.

[9]For informal collaboration networks in Financial Economics, Andrikopoulos and Economou (2015) study editorial board interlocks in 20 finance journals. Andrikopoulos and Economou (2016) analyze the network of acknowledgements in financial research with a sample including all research articles in *JF*, *JFE*, *RFS*, and the Journal of Financial and Quantitative Analysis. In particular, *JFE* exhibits a small-world network. Rose and Georg (2019) exploit a novel dataset obtained from the acknowledgements of over 5,000 published papers in Financial Economics. They find that a researcher's position in the network predicts her future productivity.

inter-institutional scientific collaboration networks in materials science. However, they do not examine network growth through collaboration, especially cross-affiliation. And they do not provide a theoretic explanation for the scale-free property. We characterize the degree distribution, collaboration patterns, and growth mechanisms of the collaboration network of research institutions in Financial Economics. We propose a model of network growth to explain the emergence of scaling in the network. The model also provides a quantitative understanding towards the forces shaping the allocation of top journal publications.

The rest of the paper is organized as follows. Section 2 presents the definition of a power law. Section 3 describes the data and econometric approaches. Section 4 discusses the empirical results. Section 5 proposes an explanation of the empirical power laws, based on an accelerated network model. Section 6 concludes.

2. The Power Law

A power law, also referred to as a scaling law or a Pareto law, for a random variable x is a distribution described by the density function

$$f(x) = \frac{\alpha}{x_{\min}} \left(\frac{x}{x_{\min}} \right)^{-\alpha-1}, \quad x \geq x_{\min}, \alpha > 0, \tag{1}$$

where α is the power exponent and $x_{\min}$ is the lower bound to the power law behavior. To avoid divergence as $x \to 0$, we require $x_{\min} > 0$. The countercumulative distribution function is defined to be $\bar{F}(x) = \Pr(X > x)$. We have

$$\bar{F}(x) = \int_x^\infty f(z)dz = \left(\frac{x}{x_{\min}} \right)^{-\alpha}. \tag{2}$$

Due to the form of the countercumulative distribution function, it is sometimes referred to as a rank-size rule.

In the following, we provide a first characterization of the distributions of top finance journal publications on the institution level. Power laws prove to adequately describe these distributions in the upper tail.

3. Data and Empirical Methods

3.1 Data

We manually collect the author and affiliation information of all articles published in the top-three finance journals by reading the title page of each paper. We exclude notes, comments/replies, and speeches/addresses. We focus on a sample since 1995, which embodies the fast growth of cross-affiliation in financial research as shown in Figure 1. Until 2016, we register 4796 articles associated with 10910 author counts and 13548 affiliation counts. Both counts are with repetitions, that is, each mentioning of an author or institution contributes one count to its own category.[10] The total affiliation counts are then sorted and ascribed to the 828 distinct institutions.[11] We simply treat the counts as the institutions' numbers of publications because they naturally pick up the effect of cross-affiliation and give full scope to collaboration.[12]

[10] For a specific example, Edmans et al. (2012) supply the following acknowledgement of the affiliations of the authors on the title page of the *JF* article: "Edmans is from The Wharton School, University of Pennsylvania, NBER, and ECGI; Gabaix is from the NYU Stern School of Business, NBER, CEPR, and ECGI; Sadzik is from New York University; and Sannikov is from Princeton University." In our sample, this paper consists of four authors affiliated with six distinct institutions. And we count one publication for University of Pennsylvania, two for NBER, one for CEPR (Center for Economic and Policy Research), two for ECGI (European Corporate Governance Institute), two for New York University, and one for Princeton University.

[11] We identify distinct institutions using English translations in cases where the affiliations are reported in non-English languages.

[12] Similarly, Newman (2004), in the context of coauthor networks, provides the simplest method of counting the frequency of coauthorship between pairs of individual scientists as a measure of the

3.2 Empirical Methods

A power law model and the lower bound to the power law behavior can be determined adaptively. Given the cutoff for points in the upper tail, we get the measured data $x_1 \geq x_2 \geq ... \geq x_N = x_{min}$ with N observations. We estimate $\widehat{\alpha}$ as the slope of the OLS log-log regression (Gabaix and Ibragimov, 2011):

$$\ln(n - \gamma) = constant - \widehat{\alpha} \ln x_n + noise, \tag{3}$$

where γ is an adjustment to the rank n. $\gamma = 0$ is typical in the literature while $\gamma = 1/2$ is optimal. The downward adjustment of 1/2 to the rank reduces the small-sample bias to the leading order for the log-log regression.[13] The asymptotic standard error of $\widehat{\alpha}$ is computed at $\widehat{\alpha} \cdot (N/2)^{-1/2}$, not the conventional OLS standard error that is nullified by the positive autocorrelation introduced by the ranking procedure into the residuals.

The lower bound now hinges on a tradeoff: Too high $x_{\min}$ will leave out legitimate data points thus increase finite sample biases, while too low $x_{\min}$ introduces biases by mixing with non-power-law data. We adopt the approach proposed by Clauset, Shalizi, and Newman (2009), which chooses $x_{\min}$ to minimize the distance between the empirical distribution of the data and the fitted power law. We measure the distance using the Kolmogorov-Smirnov statistic, D_{KS}, which is most common for nonmormal data:

$$D_{KS} = \max_{x \geq x_{min}} |P(x) - F(x)|, \tag{4}$$

where $P(x)$ and $F(x)$ are the CDFs of the data and the fitted power law model, respectively. Our method avoids the subjectivity in applying some upper quantile or

strength of collaboration.

[13]Barro and Jin (2011) impose the same downward adjustment prescribed by Gabaix and Ibragimov (2011) when estimating their power laws for the macroeconomic disasters.

visual checks to fix $x_{\min}$ as often done in the literature (see, e.g., Beirlant et al., 2004 and Drees, De Haan, and Resnick, 2000), while other more subtle methods require estimation of extra parameters (Embrechts, Kluppelberg, and Mikosch, 1997).

A two-parameter distribution, such as the lognormal, may provide a better fit for the data due to the added curvature from the free parameter (Eeckhout, 2004). To test potential deviations from a power law, we employ the Gabaix-Ibragimov test (Gabaix and Ibragimov, 2008) which augments the OLS regression with a quadratic term:

$$\ln(n-1/2) = constant - \widehat{\alpha}\ln x_n + \widehat{\beta}(\ln x_n - \bar{x})^2 + noise, \tag{5}$$

where $\bar{x} \equiv cov((\ln x_n)^2, \ln x_n)/var(\ln x_n)/2$. $\bar{x}$ recenters $\ln x_n$ such that $\widehat{\alpha}$ stays the same, irrespective of the quadratic term. The standard error of the test statistic $\widehat{\beta}$ is computed at $\widehat{\alpha}^2 \cdot (2N)^{-1/2}$. We reject the null of an exact power law if and only if $\widehat{\beta}$ is statistically different from zero.

4. Empirical Findings

We show in Panel A of Figure 2 the distribution of top finance journal publications accumulated to the end of 2016 for all institutions. We plot the rank of the institutions against their total publications in log-log coordinates. We impose the optimal downward adjustment of 1/2 to the rank as suggested by Gabaix and Ibragimov (2011). The upper tail of the distribution falls onto a straight line that hints at a power law, or a rank-size rule, as dictated by (2).

Applying the method discussed in the previous section, we retain the 50 most prolific institutions in the upper tail, with the estimated cutoff of $x_{min} = 71$. We report the complete list of the 50 institutions together with their publication records in Table 1.

Although the 50 institutions account for merely 6.0% of the entire sample of institutions that had published in top finance journals during our sample period, they contribute a predominant 61.3% of total publications. The distribution of the 50 institutions is highly right-skewed, with a mean number of publications of 166 and a median of 112; notably, NBER is solely responsible for 1105 publications.

We classify the 50 institutions according to several criteria in Table 2. The comprehensiveness of our sample is revealed by the scattering of the institutions across type, geographic region, and time of establishment. For instance, the majority of the most productive institutions, as expected, are universities and colleges. Meanwhile, we find that three research bureaus/centers (NBER, CEPR (Centre for Economic Policy Research), and ECGI (European Corporate Governance Institute)), the Federal Reserve Board, and the Federal Reserve Bank of New York also make their way into the upper tail of the distribution. It is clear from the table that the present study broadly includes all institutions that embark on academic research in Financial Economics as "research institutions".

We present the distribution of the 50 most prolific institutions in Panel B of Figure 2. A power law model describes the data well (for over two decades of institutions and from 10^1 to 10^3 publications). We report the OLS regression results in Table 3. For the three journals combined, the regression R^2 is as high as 98.6%. The power exponent is estimated at 1.640 with a standard error of 0.328. As a robustness check, we repeat the analysis for the preceding five years, from 2011 to 2015. The results are presented in Table 4. The power exponent was fairly stable, even though the average number of publications increased dramatically over time. The complex system of institutions, with diverse natures and worldwide origins, seems to have reached a scale-free stationary state.

To explore the unanimity of the power law behavior, we redo the graph of the upper tail distribution for each journal separately in Panel C of Figure 2. Since the three journals publish different total numbers of articles, we normalize each institution's publications in one journal by the average number of publications in that journal. If the same power law permeates all three journals, we expect their graphs to collapse onto one another after normalization. This is confirmed in Panel C of Figure 2. Moreover, Table 3 shows that, for each journal separately, the regression R^2 is no less than 96.1%, and the power exponent ranges from 1.490 to 1.689 with no statistically significant differences among those estimates given the standard errors.

We present in Table 5 the results of the Gabaix-Ibragimov test for deviations from our proposed power law models. For all the three journals, separately or combined, we see that $\widehat{\beta}$ is not significantly different from zero given the standard errors. We fail to significantly improve model performance by introducing curvature to the models.

For a final robustness check, we apply the well-known tail-index estimator of Hill (1975) to our empirical data. The estimator is

$$\widehat{\alpha}^H = \left(\frac{1}{N-1} \sum_{n=1}^{N-1} (\ln x_n - \ln x_N) \right)^{-1}, \tag{6}$$

with a standard error of $\widehat{\alpha}^H N^{-1/2}$.[14] We use the Kolmogorov-Smirnov test of the empirical CDF against the Hill's estimate to detect potential deviations from power laws. We present the results for model estimation in Panel A and model tests in Panel B of Table 6. We confirm that, although some variations in the results are unavoidable when we apply different estimation methods, we find no qualitative differences in the results

[14]Under the null of a perfect power law, the Hill's estimator exploits the efficiency properties of maximum likelihood estimation, and hence provides a smaller standard error than that of Gabaix and Ibragimov (2011). However, it can also underestimate the true estimation error in finite samples in the presence of bias terms. For further discussions, see, e.g., Gabaix and Ioannides (2004).

under either the OLS log-log regression or the Hill's tail-index estimator approach. Specifically, the discrepancies in the power exponent estimates are not statistically significant given the standard errors for the power law models considered. Furthermore, the Kolmogorov-Smirnov test cannot reject the power law models at a conventional significance level.

In sum, the proposed power laws seem to succinctly capture growth in the research output of institutions. We now turn to examine the dynamics and evolution of collaboration patterns in Financial Economics, which may reveal generic mechanisms that engender the scaling laws documented here.

5. A Model of Accelerated Networks

A variety of processes can explain the emergence of scaling (see, e.g., Barabási and Albert, 1999; Gabaix, 1999; and Ferrer i Cancho and Solé, 2003).[15] We find empirical support for the network model of Barabási and Albert (1999), who pioneer two generic mechanisms: One is *growth*, that is, new nodes continue entering the network; the other is *preferential attachment*, also referred to as *success-breeds-success*, *popularity-is-attractive*, *rich-get-richer*, or *the Matthew effect*, that is, a node with a higher degree will enjoy a cumulative advantage and acquire even more links in the future.[16]

Specifically, we treat institutions with at least one top finance journal publication as nodes in our collaboration network. Therefore, an institution joins the network when it publishes for the first time in the top finance journals. And we treat the total number of publications of a node as the degree of the node. In concert with our

[15]For textbook treatments on the topic, see Dorogovtsev and Mendes (2003), Jackson (2008), Barabási (2016), and Newman (2018), among others.

[16]Preferential attachment also plays an important role in recent coauthorship network formation models. See, e.g., Hsieha et al. (2018) and Anderson and Richards-Shubik (2019).

data acquisition method, we increase the degree of a node by one per citation of the corresponding institutional affiliation by an author in an article. We plot in Figure 3 the structure of the collaboration network at the end of 2016. Two nodes are connected if the corresponding two institutions work together in at least one publication during 1995-2016. Notably, the network has a giant component that includes 99.5% of the nodes, which reveals the close linkage among the academic society for financial research. The most connected node is NBER, which has collaborated with 300 other institutions during our sample period. In contrast, the average number of collaborating institutions for all nodes in the network is 13.5.[17] Hence the average number of collaborators is small relative to that of the most connected "star".[18]

5.1 Dynamic Patterns

We first examine the growth of the collaboration network of financial research institutions. We plot in Panel A of Figure 4 the number of nodes newly joining the network. We see that the growth of the nodes is stable, with certain fluctuations around the financial crisis of 2008. Panel B of Figure 4 presents the fraction of publications contributed by the new nodes for each year from 1995 to 2016. This proportion again stays relatively stable, with an average of 6.0% from 2000 to 2016.

We then investigate the allocation of new links (publications) to the nodes. Exact power laws follow only from *linear* preferential attachment (Krapivsky, Redner, and Leyvraz, 2000). That is, the probability for an existing node to acquire new links

[17]In comparison, Goyal, van der Leij, and Moraga-González (2006) show that the giant component in their coauthor network consists of up to 40.7% of the nodes in the 1990s. The most connected economist has 54 coauthors while the average number of coauthors is 1.7 in the 1990s.

[18]Our focus in this study is on the degree distribution under which two nodes are allowed to have multiple links between them. Although Figure 3 provides a simple and intuitive visualization of the collaboration patterns among the institutions, it is difficult to do a similar plotting in the presence of multi-links. For this reason, we here do not further discuss other statistics, like the average distance and clustering coefficient, of the network.

($\Pi(k)$) is proportional to its degree (k), or $\Pi(k) \sim k$. Exploiting the network maps at the end of each year from 1995 to 2016, we use the method provided in Jeong, Néda, and Barabási (2003) to measure preferential attachment. We provide detailed results in Appendix A. We find that $\Pi(k)$ can be well approximated by $\Pi(k) \sim k^{\theta}$, where θ is estimated at 1.00 with a standard error of 0.08. Thus, linear preferential attachment achieves a good match for data.

In the following, we develop a network model that captures three additional features of the collaboration network. First, expanding coauthorship (Panel A of Figure 1) and cross-affiliation (Panel B of Figure 1) generate nonlinear growth in total publications. Thus, instead of linear growth considered by Barabási and Albert (1999), we incorporate accelerated growth following Dorogovtsev and Mendes (2001b, 2003). Second, we include internal links because 94.0% of the total publications come from collaboration among already existing nodes (Ghoshal, Chi, and Barabási, 2013). Third, although preferential attachment enables institutions successful in historic records to produce even more research output in the future, we randomly allocate a fraction of new publications to the existing nodes, allowing research opportunities to strike institutions by sheer chance (Ghoshal, Chi, and Barabási, 2013).[19]

5.2 An Evolving Network with Accelerated Growth

Consider discrete time $t = 0, 1, 2, ...$, with time interval Δt. Assume that there is one node in the network at time 0 and that one new node enters the network at each $t \geq 1$. Then there are t nodes in the network at time t, excluding the new node entering at the time. Let $m(t)$ denote the publication rate at time t. Hence $m(t)\Delta t$ is the total

[19]Mele (2017) develops a structural model of network formation, with both strategic and random networks features, which generates directed dense networks. He also provides a Bayesian MCMC method to estimate model parameters.

number of new publications during the time interval $[t, t+1]$. These publications are distributed among all nodes in the network at time $t+1$. We assume that, a faction c_0 of the total publications is distributed *preferentially* to the existing nodes, a fraction c_1 is distributed *randomly* (with equal probability $1/t$) to the existing nodes, and a fraction c_2 is allocated to the new node. The constants c_0, c_1, and c_2 are nonnegative and sum to one.[20] Preferential and random allocations are independent events.

Let $X_{s,t}$ denote the degree at time t of a node entering at time s. Notice that

$$\begin{aligned}
&\Pr(X_{s,t+1} = k) = \sum_{j \geq 0} \Pr(X_{s,t+1} = k, X_{s,t} = j) \\
&\quad = \Pr(X_{s,t+1} = k | X_{s,t} = k - (c_0 + c_1)m(t)\Delta t) \Pr(X_{s,t} = k - (c_0 + c_1)m(t)\Delta t) \\
&\quad + \Pr(X_{s,t+1} = k | X_{s,t} = k - c_1 m(t)\Delta t) \Pr(X_{s,t} = k - c_1 m(t)\Delta t) \qquad (7) \\
&\quad + \Pr(X_{s,t+1} = k | X_{s,t} = k - c_0 m(t)\Delta t) \Pr(X_{s,t} = k - c_0 m(t)\Delta t) \\
&\quad + \Pr(X_{s,t+1} = k | X_{s,t} = k) \Pr(X_{s,t} = k).
\end{aligned}$$

The four conditional probabilities in the above equation can be evaluated by linear preferential attachment, random allocation, and independence of the events.

Let $q(k, s, t) = \Pr(X_{s,t} = k)$ denote the probability that the node has degree k at time t, $t \geq s$. A new node entering at time s obtains the degree $c_2 m(s-1)\Delta t$. Thus, $q(c_2 m(s-1)\Delta t, s, s) = 1$. We have the following master equation for degree

[20]For simplicity, we assume $m(0)\Delta t$ goes to the only node at $t = 0$ in the network.

probabilities of individual nodes.

$$
\begin{aligned}
q(k,s,t+1) = {} & \frac{k-(c_0+c_1)m(t)\Delta t}{A(t)}\frac{1}{t}q(k-(c_0+c_1)m(t)\Delta t,s,t) \\
& + \left(1-\frac{k-c_1m(t)\Delta t}{A(t)}\right)\frac{1}{t}q(k-c_1m(t)\Delta t,s,t) \\
& + \frac{k-c_0m(t)\Delta t}{A(t)}\left(1-\frac{1}{t}\right)q(k-c_0m(t)\Delta t,s,t) \\
& + \left(1-\frac{k}{A(t)}\right)\left(1-\frac{1}{t}\right)q(k,s,t), \quad s\le t,\ t=1,2,...,
\end{aligned}
\tag{8}
$$

where $A(t)=\sum_{s=0}^{t-1}m(s)\Delta t$ is the cumulative degrees of all nodes at t. It is worth mentioning that $k\le A(t)$, that is, the degree of a node at time t is not greater than the cumulative input of degrees until time t. Re-arrange the terms of (8), we have:

$$
\begin{aligned}
\frac{q(k,s,t+1)-q(k,s,t)}{\Delta t} = {} & \frac{1}{tA(t)\Delta t}((k-(c_0+c_1)m(t)\Delta t)q(k-(c_0+c_1)m(t)\Delta t,s,t) \\
& -(k-c_1m(t)\Delta t)q(k-c_1m(t)\Delta t,s,t)) \\
& + \frac{1-1/t}{A(t)\Delta t}((k-c_0m(t)\Delta t)q(k-c_0m(t)\Delta t,s,t)-kq(k,s,t)) \\
& + \frac{1}{t\Delta t}(q(k-c_1m(t)\Delta t,s,t)-q(k,s,t)).
\end{aligned}
$$

To exploit the tractability of the rate-equation approach (Dorogovtsev, Mendes, and Samukhin, 2000; Krapivsky and Redner, 2002), we let Δt go to zero as time t and degree k vary continuously. Suppose the degree rate function $m(t)$ is continuous. The continuous-time approximation of the master equation (8) is obtained as follows. For $t>s\ge 0$,

$$
\frac{\partial p(k,s,t)}{\partial t}+\frac{c_0m(t)}{A(t)}\frac{\partial kp(k,s,t)}{\partial k}+\frac{c_1m(t)}{t}\frac{\partial p(k,s,t)}{\partial k}=0, \tag{9}
$$

where $p(k,s,t)$ is a generalized probability density function representing the density of the degree distribution at time t of the node s. The initial condition is $p(k, s, s) = \delta(k - c_2 m(s))$ for $s > 0$, where $\delta(\cdot)$ is the delta function with the properties $\delta(0) = \infty$, $\delta(x) = 0$ for $x \neq 0$, and $\int_0^\infty \delta(k - k_0) dk = 1$ for a non-negative constant k_0.

Multiplying by k and integrating from 0 to ∞ with respect to k for the above equation, we obtain:

$$\frac{\partial \int_0^\infty k p(k, s, t) dk}{\partial t} = \frac{c_1 m(t)}{t} + \frac{c_0 m(t) \int_0^\infty k p(k, s, t) dk}{A(t)}. \tag{10}$$

Denote the average degree $\bar{k}(s, t) = \int_0^\infty k p(k, s, t) dk$. Then we obtain the evolution equation for $\bar{k}(s, t)$:

$$\frac{\partial \bar{k}(s, t)}{\partial t} = \frac{c_1 m(t)}{t} + \frac{c_0 m(t) \bar{k}(s, t)}{A(t)}, \tag{11}$$

with boundary condition $\bar{k}(s, s) = \int_0^\infty k p(k, s, s) dk = c_2 m(s)$.

The integration $\int_0^t p(k, s, t) ds$ is the total number of nodes with degree k at time t, and t is the number of nodes at time t, excluding the newly coming one. Hence the degree distribution at time t is given by $P(k, t) = \frac{1}{t} \int_0^t p(k, s, t) ds$. Actually, the distribution $P(k, t)$ can be recovered from $\bar{k}(s, t)$ by the relation

$$P(k, t) = \frac{1}{t} \int_0^t \delta(k - \bar{k}(s, t)) ds = -\frac{1}{t} \left(\frac{\partial \bar{k}(s, t)}{\partial s} \right)^{-1} \Bigg|_{s = \hat{s}(k, t)}, \tag{12}$$

where $s = \hat{s}(k, t)$ is a solution to the equation $k = \bar{k}(s, t)$. The first equality is due to the fact that the solution $p(k, s, t)$ is actually a delta function $p(k, s, t) = \delta(k - k_s)$ for some k_s and the second equality is according to the general property of the delta function.

We now turn to solve the equation (11). A general solution for $\bar{k}(s,t)$ is

$$\bar{k}(s,t) = \left(C(s) + \int_1^t \frac{c_1 m(v)}{v} \left(\int_0^v m(u)du \right)^{-c_0} dv \right) \left(\int_0^t m(v)dv \right)^{c_0}. \tag{13}$$

By the boundary condition $\bar{k}(s,s) = c_2 m(s)$, $C(s)$ can be identified and we obtain

$$\bar{k}(s,t) = c_2 m(s) \left(\frac{\int_0^s m(v)dv}{\int_0^t m(v)dv} \right)^{-c_0} + \int_s^t \frac{c_1 m(v)}{v} \left(\frac{\int_0^v m(u)du}{\int_0^t m(u)du} \right)^{-c_0} dv. \tag{14}$$

Recall that $\bar{k}(s,t)$ is the average degree at time t of the nodes entering at time s. The above equation indicates that a lower s corresponds to a higher $\bar{k}(s,t)$ for a fixed t.

Let $s = \hat{s}(k,t)$ be a solution to the equation $\bar{k}(s,t) = k$. Then $\bar{k}(\hat{s}(k,t),t) = k$. Taking partial derivative with respect to k, it follows that

$$\frac{\partial \bar{k}}{\partial k} = \left. \frac{\partial \bar{k}}{\partial s} \right|_{s=\hat{s}} \frac{\partial \hat{s}}{\partial k} = 1. \tag{15}$$

Hence

$$\left. \frac{\partial \bar{k}}{\partial s} \right|_{s=\hat{s}} = \left(\frac{\hat{s}}{\partial k} \right)^{-1},$$

where $\hat{s} = \hat{s}(k,t)$ satisfies

$$k = c_2 m(\hat{s}) \left(\frac{\int_0^{\hat{s}} m(v)dv}{\int_0^t m(v)dv} \right)^{-c_0} + \int_{\hat{s}}^t \frac{c_1 m(v)}{v} \left(\frac{\int_0^v m(u)du}{\int_0^t m(u)du} \right)^{-c_0} dv. \tag{16}$$

Next we introduce an assumption on the rate function $m(t)$ in order to evaluate $\partial \bar{k}(s,t)/\partial s$. Suppose that $m(t)$ is a non-negative continuous function defined on $[0,\infty)$.

Assumption: There exist constants $\gamma \geq 0$, $b \geq a > 0$, such that $as^\gamma \leq m(s) \leq bs^\gamma$ for all $s > 0$.

For example, $m(s) = m$ or $m(s) = ms^{\gamma}$ for some positive constant m, satisfies the assumption.[21] Clearly, when the assumption is satisfied, $m(s)$ is such a function that $\limsup_{s\to\infty} \frac{m(s)}{s^{\gamma}}$, $\liminf_{s\to\infty} \frac{m(s)}{s^{\gamma}}$, $\limsup_{s\to 0^+} \frac{m(s)}{s^{\gamma}}$, and $\liminf_{s\to 0^+} \frac{m(s)}{s^{\gamma}}$ all exist. We write $h(s) = O(s^{\gamma})$ if a continuous function $h(s)$ satisfies the assumption. We can directly show that $\int_0^s h(\nu)d\nu = O(s^{\gamma+1})$ if $h(s) = O(s^{\gamma})$.

Using the above assumption, we can estimate the right hand side of (14). We find that

$$k = f(t)O(\hat{s})^{\gamma - c_0(1+\gamma)} + g(t), \tag{17}$$

where

$$\begin{aligned} f(t) &= (c_2 - \frac{c_1}{\gamma - c_0(1+\gamma)})\left(\int_0^t m(v)dv\right)^{c_0} = O(t)^{c_0(1+\gamma)}, \\ g(t) &= \frac{c_1}{\gamma - c_0(1+\gamma)}\left(\int_0^t m(v)dv\right)^{c_0} O(t^{\gamma - c_0(1+\gamma)}) = O(t)^{\gamma}. \end{aligned}$$

Thus, $\hat{s} = (f(t))^{-1}O(k - g(t))^{\frac{1}{\gamma - c_0(1+\gamma)}}$ and

$$\frac{\partial \hat{s}}{\partial k} = \frac{(f(t))^{-1}O(k - g(t))^{-\left(1 - \frac{1}{\gamma - c_0(1+\gamma)}\right)}}{\gamma - c_0(1+\gamma)} = \frac{f(t)^{-1}O(k)^{-\left(1 - \frac{1}{\gamma - c_0(1+\gamma)}\right)}}{\gamma - c_0(1+\gamma)}. \tag{18}$$

The second equality in the above equation holds when k is large and has the same or a higher order than $O(t)^{\gamma}$ of $g(t)$. Note that the total degree $\int_0^t m(v)dv$ has an order of $O(t)^{1+\gamma}$ thus the average degree $\frac{1}{t}\int_0^t m(v)dv$ has an order of $O(t)^{\gamma}$. Finally, it follows

[21] Network growth has important implications for the degree distribution. Exponential network growth is examined by, among others, Dorogovtsev and Mendes (2001a), Parolo et al. (2015), and Sun, Medo, and Staab (2020).

from (15) and (12) that the degree distribution at time t is

$$P(k,t) = t^{-1} f(t)^{-1} O(k)^{-\left(1+\frac{1}{c_0(1+\gamma)-\gamma}\right)}, \tag{19}$$

or

$$P(k,t) \sim k^{-\left(1+\frac{1}{c_0(1+\gamma)-\gamma}\right)}, \tag{20}$$

when k is large. Therefore, the degree distribution obeys a power law in the upper tail with exponent

$$\alpha = \frac{1}{c_0(1+\gamma)-\gamma}. \tag{21}$$

To ensure the existence of $\bar{k}$, we require $1+\alpha > 2$ or $1 > c_0 > \frac{\gamma}{1+\gamma}$.

5.3 Model Implications

The power exponent is determined by the fraction of preferential allocation and the order of growth of the network. From (21), the exponent α decreases in c_0. The larger proportion of degree allocation according to preferential attachment heightens the success-breeds-success effect and enhances the dispersion of the degree distribution. Suppose that c_0 is strictly less than 1. Then α increases in γ. Heterogeneity of the system diminishes as the network undergoes higher order growth. Intuitively, preferential attachment works by cumulative advantages that are tempered by more and more publications to be allocated in the futures. As the number of nodes grows linearly in time, higher-order nonlinear growth of degrees has to be generated through more and more extensive collaboration across all the nodes. At the extreme, every article would be authored by all institutions altogether, hence each institution would have the same number of publications. Put differently, at the limit of $\gamma \to c_0/(1 - c_0)$, the power law collapses and heterogeneity of the nodes disappears. c_1 and c_2 do not directly enter (21), but they indirectly affect α through c_0 as $c_0 + c_1 + c_2 = 1$. For $c_0 \to 1^-$, we get $\alpha \to 1^+$, a special case called Zipf's law, which is interesting because all its moments diverge. γ does not play a role in this case. We obtain the Barabási and Albert model in the special case of $c_0 = c_2 = 0.5$ and $\gamma = 0$.

For our collaboration network, the total counts of new publications equal the product of the number of articles, the average number of authors per paper, and the average number of affiliations per author. Coauthorship and cross-affiliation exhibit approximately linear growth, suggesting the quadratic growth of $m(t)$ with $\gamma = 2$, given that the total number of articles published annually remains stable in the long run. Our empirical study finds that $\widehat{\alpha} = 1.64$ for the three journals altogether. We can use (21) to obtain $c_0 = 87.0\%$. That is, 87.0% of publications may have resulted from success-breeds-success, a dominating channel for the distribution of the top journal publications. We have deduced from the data that 6.0% of publications go to new nodes. Random allocation thus takes the remaining 7.0% of publications. When we lack either the growth of coauthorship or the growth of cross-affiliation, γ is brought down to 1, which implies $c_0 = 80.5\%$ under slowed acceleration; additionally, when we lack both forms of collaboration, we have $\gamma = 0$ and $c_0 = 61.0\%$ under linear growth. This comparison emphasizes the importance of identifying the collaboration patterns before further inference on the evolving network.

A most commonly invoked measure of dispersion/inequality in studies of income or wealth distributions is the Gini coefficient (G). $G = 0$ represents perfect equality while $G = 1$ stands for the other extreme of maximal inequality. Dispersion increases with G monotonically in between. $G = 0.5$ is commonly regarded as the warning level for great disparity. We here borrow this measure and provide further discussions on the heterogeneity of the institutions. For power law distributions, it is well-known that $G = 1/(2\alpha - 1)$ (Aaberge, 2005). For the three journals altogether, we have $G = 0.44$ for $\widehat{\alpha} = 1.64$. Given $c_0 = 87.0\%$, $c_1 = 7.0\%$, and $c_2 = 6.0\%$, when either the growth of coauthorship or the growth of cross-affiliation is absent, α reduces to 1.35 implying $G = 0.59$. And again, given the shares, when both forms of collaboration are absent, α reduces to 1.15 implying $G = 0.77$. Thus, higher order growth in collaboration effectively diminishes heterogeneity in the institutions' research output.

5.4 Further Discussions

It is now standard for the accelerated network models to consider two additional components: *fitness* and *aging*. Specifically, Bianconi and Barabási (2001) consider the degree of a node as a proxy for its experience, and provide a method to identify the fitness (talent) of a node. For instance, the fitness of an institution in our study may be the endowment, scale, location, pedigrees of the employees, etc., of the institution. All these factors may potentially determine the institution's future research performance. Kong, Sarshar, and Roychowdhury (2008) find that the fitnesses of webpages are exponentially distributed, which explain the power law degree distributions of webpages and the quick rising of interesting new pages in the page ranking. Dorogovtsev, Mendes, and Samukhin (2000) investigate the effect of aging, which captures the natural preference for the new and moderates the success-breeds-success effect. Medo, Cimini, and Gualdi (2011) and Sun, Staab, and Karimi (2018) show that temporal effects have important implications for network growth. The product of fitness and aging is called the "*relevance*" of a node in the literature (Medo, Cimini, and Gualdi, 2011). Under the combined effects of experience (rich-get-richer), fitness (fitter-get-richer), and aging (younger-get-richer), new degrees are then allocated preferentially according to the product of experience and relevance.[22] However, we apply similar methods and do not find significant differences in the relevance of the research institutions in our study.[23] We thus do not pursue extensions of our model along this dimension.

To obtain a power exponent (α) greater than 1, Dorogovtsev and Mendes (2001b) introduce a time-dependent "*additional attractiveness*"[24] to the nodes, which may not be easily verified empirically (Jeong, Néda, and Barabási, 2003). Our model achieves the scaling property of networks with nonlinear growth without this extra assumption. Note that the effect of additional attractiveness diminishes as the degree of a node becomes larger since it is additive, while the effects of fitness and aging do not since they are multiplicative. Accordingly, small differences in relevance could result in large gaps in the degrees of nodes even in the short run.

To sum up, we make three main contributions in our model analysis. First, we provide a model which encompasses a rich set of dynamic patterns of network growth. Although some of these features have been separately examined in previous studies, we synthesize them with a tractable model and closely examine the interaction between different model mechanisms. Second, we focus on general polynomial network growth, motivated by the collaboration patterns in financial research, even though exponential growth has been extensively studied in the literature. Our modeling approach could potentially be applied to investigate other networks with polynomial growth. Third, we exploit our theoretic results to develop understanding towards the production of scientific knowledge in financial research, and reveal the important role played by collaboration, through both coauthorship and cross-affiliation, in balancing the research

[22] That is, $\Pi(k_i) \sim F_i k_i D(\tau_i)$, where F_i is the fitness of node i, τ_i is the age of node i, and $D(\cdot)$ is a decreasing function that represents the temporal decay of relevance.

[23] The results are available upon request.

[24] That is, $\Pi(k_i) \sim k_i + A_i$, where A_i is the additional attractiveness of node i.

output of institutions.

6. Conclusion

Institutions are fundamental units in which research activities are organized and conducted. In this paper, we document the recent fast development of cross-affiliation of researchers who publish in the top finance journals from 1995 to 2016, and the resulting highly nonlinear growth of research output following mixed forms of collaboration. We show that scale-free power laws characterize the distributions of worldwide institutions' top finance journal publications. We propose an accelerated network model to explain the scale-invariance. We investigate the growth mechanisms of the network and find that linear preferential allocation of new publications plays a key role in the emergence of the scaling behavior. We consider three distinct ways by which new publications are generated, in particular, through new nodes (institutions publishing for the first time in top finance journals), random allocation, and preferential allocation. The last channel accounts for a dominant 87.0% of all publications. Our theoretic analysis also demonstrates that higher order growth of the network, possibly originating from new forms of collaboration, reduces the dispersion in the institutions' cumulative research output.

The cross-affiliation and power law distributions we focus on here may characterize other fields and extend to a broader set of journals as well. Cross-field examinations of the scaling behavior and the role played by preferential attachment in the allocation of publications could undoubtedly enrich our understanding of production of scientific knowledge on the institution level. We can also examine the inverse relationship between order of growth in collaboration and heterogeneity of research institutions through cross-subfields and even cross-disciplinary studies. Furthermore, due to the obvious relations between the authors and their institutional affiliations, an interesting future direction is to reconcile the small-world properties of the coauthor network discovered on the individual researcher level and the scale-free properties of the collaboration network on the institution level. Last but not least, we have demonstrated the effect of collaboration on the distribution of research output, while we have not touched on the efficiency of such scale-free networks as a way of organizing research activities, and the robustness of such networks under attack (e.g., the accidental demise of a major research institution). Some of these works await comprehensive data to be gathered, and we leave them to future studies.

Appendix A. Measuring preferential attachment

At every time step t, a node i already present in the network acquires new links at the rate $\Pi(k_i)$ where k_i is the degree of the node. Under preferential attachment, $\Pi(k_i)$ is a monotonically increasing function of k_i. Several authors propose that Π follows a power law (Krapivsky, Redner, and Leyvraz, 2000; Newman, 2001a; Jeong, Néda, and Barabási, 2003):

$$\Pi(k_i) = \frac{k_i^{\theta}}{\sum_j k_j^{\theta}} = C_t k_i^{\theta}, \tag{A.1}$$

where $\theta > 0$ is a scaling constant; C_t is a normalization pertinent to time t. The scale-free model of Barabási and Albert (1999) corresponds to linear preferential attachment with $\theta = 1$, while for $\theta < 1$ (sub-linear), the degree distribution follows a stretched exponential and for $\theta > 1$ (super-linear), a single node connects to nearly all other nodes (Krapivsky, Redner, and Leyvraz, 2000). We use the method provided in Jeong, Néda, and Barabási (2003) to examine whether Π could be well approximated by a power law, and if so, to estimate the exponent θ.

The dynamics of the research institution network provide the time when each node joins the system and the degrees of the nodes from 1995 to 2016. If the evolving network develops a stationary state, we can use nodes already present at time T and the degrees of these nodes at both T and $T + \Delta T$ to measure Π. To ensure stationarity, we need T away from T_0 when the network starts. We also choose a small ΔT such that the effect of t is at minimum and Π relies exclusively on k. To further reduce noise, we examine the cumulative function

$$\pi(k) = \sum_{k_i=1}^{k} \Pi(k_i). \tag{A.2}$$

For $\Pi(k) \sim k^{\theta}$, we expect $\pi(k) \sim k^{\theta+1}$.

In our empirical implementation, we choose $T_0 = 1995$, T =2000-15, and $\Delta T = 1$. The $\pi(k)$ functions are shown in Panel A of Figure A.1. We plot two additional benchmark cases for comparison: $\pi(k) \sim k$ without preferential attachment and $\pi(k) \sim k^2$ for linear preferential attachment. The $\pi(k)$ functions of the network follow a straight line in log-log coordinates. Therefore, the power law form in (4) provides a good approximation. The $\pi(k)$ functions also increase with a speed consistent with linear preferential attachment, independently of the year when the measurements are taken. This result supports stationarity in the degree allocation process, even though some variation is inevitable due to statistical noise. We show the estimated θ exponent in Panel B of Figure A.1. The exponent from 2000-15 has a mean of 2.00 and a standard deviation of 0.08. Linear preferential attachment hence constitutes the key degree allocation mechanism of the growing network.

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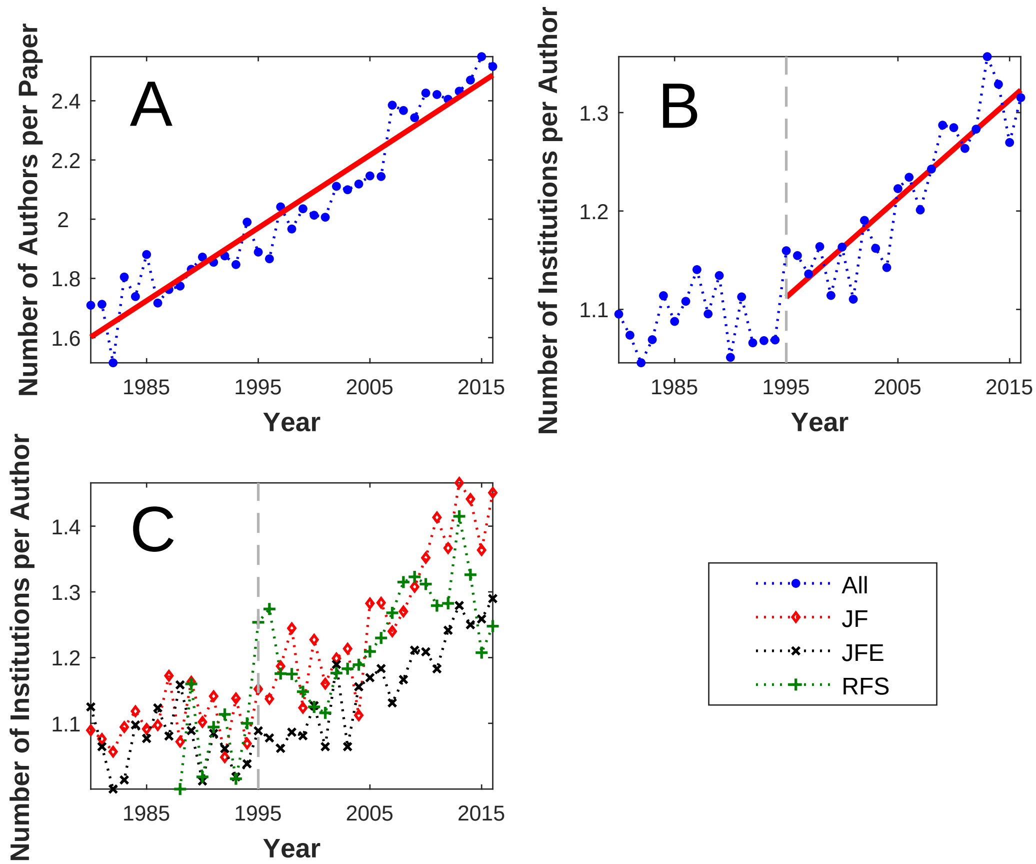

Figure 1. Coauthorship and Cross-affiliation Patterns. We graph the average number of authors reported per paper ($\bar{N}_{aut}$) and the average number of institutions reported per author ($\bar{N}_{ins}$) at top finance journals (*JF*, *JFE*, and *RFS*). Each year, we calculate $\bar{N}_{aut}$ and $\bar{N}_{ins}$ using total paper, author, and affiliation counts in that year. (**A**) $\bar{N}_{aut}$ from aggregating the top-three journals. (**B**) $\bar{N}_{ins}$ from aggregating the top-three journals. (**C**) $\bar{N}_{ins}$ separately for each journal. The first issue of *RFS* appeared in 1988. The solid lines represent linear fit and vertical lines mark the year 1995.

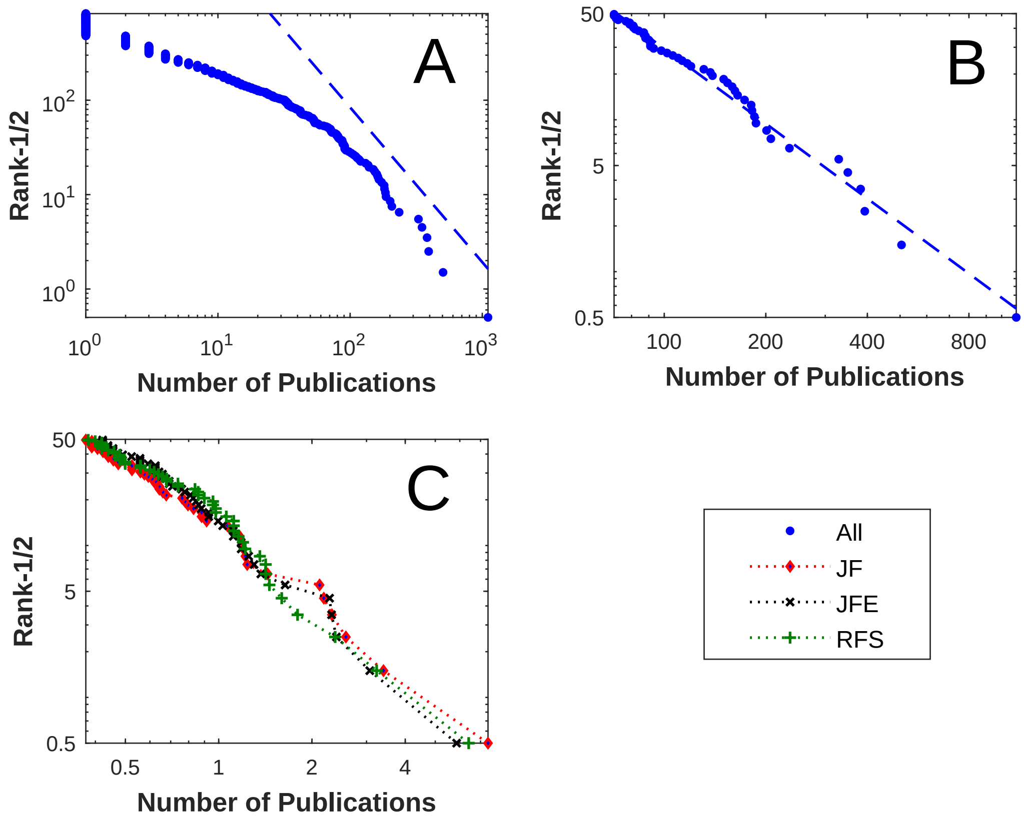

Figure 2. The Distribution Function of Institutions' Top Finance Journal Publications. (**A**) Total publications in the top-three journals (*JF*, *JFE*, and *RFS*) for all 828 institutions. (**B**) Total publications in the top-three journals for the 50 most prolific institutions. (**C**) Total publications in each of the *JF*, *JFE*, and *RFS* for the 50 most prolific institutions.

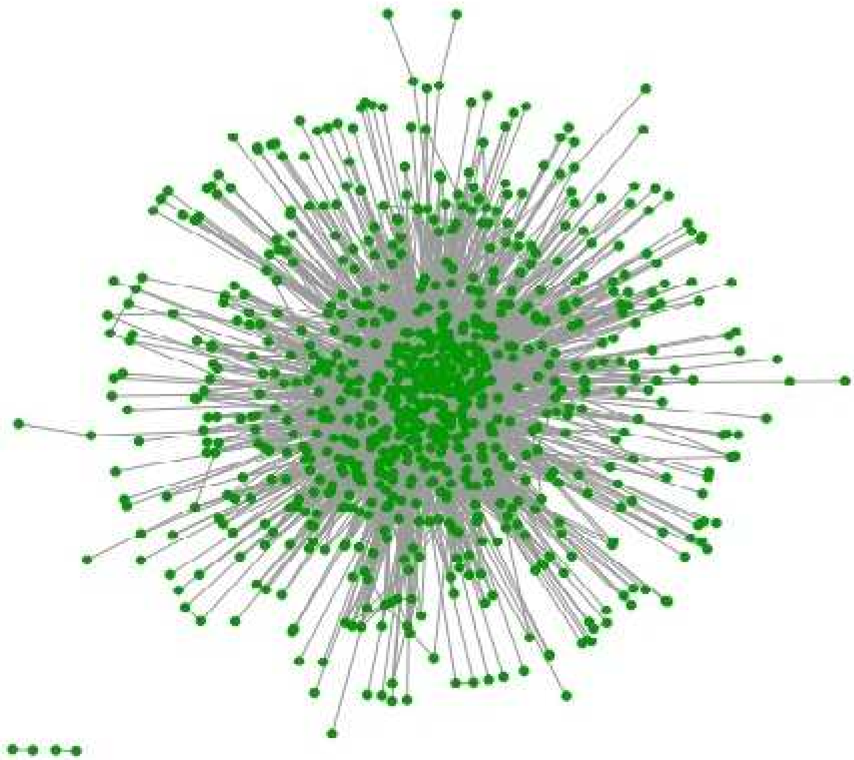

Figure 3. Collaboration Network of Institutions in Financial Economics. We link two institutions if they are simultaneously acknowledged, either by one author or different authors, in one publication from 1995 to 2016. We create the figure with the software Pajek.

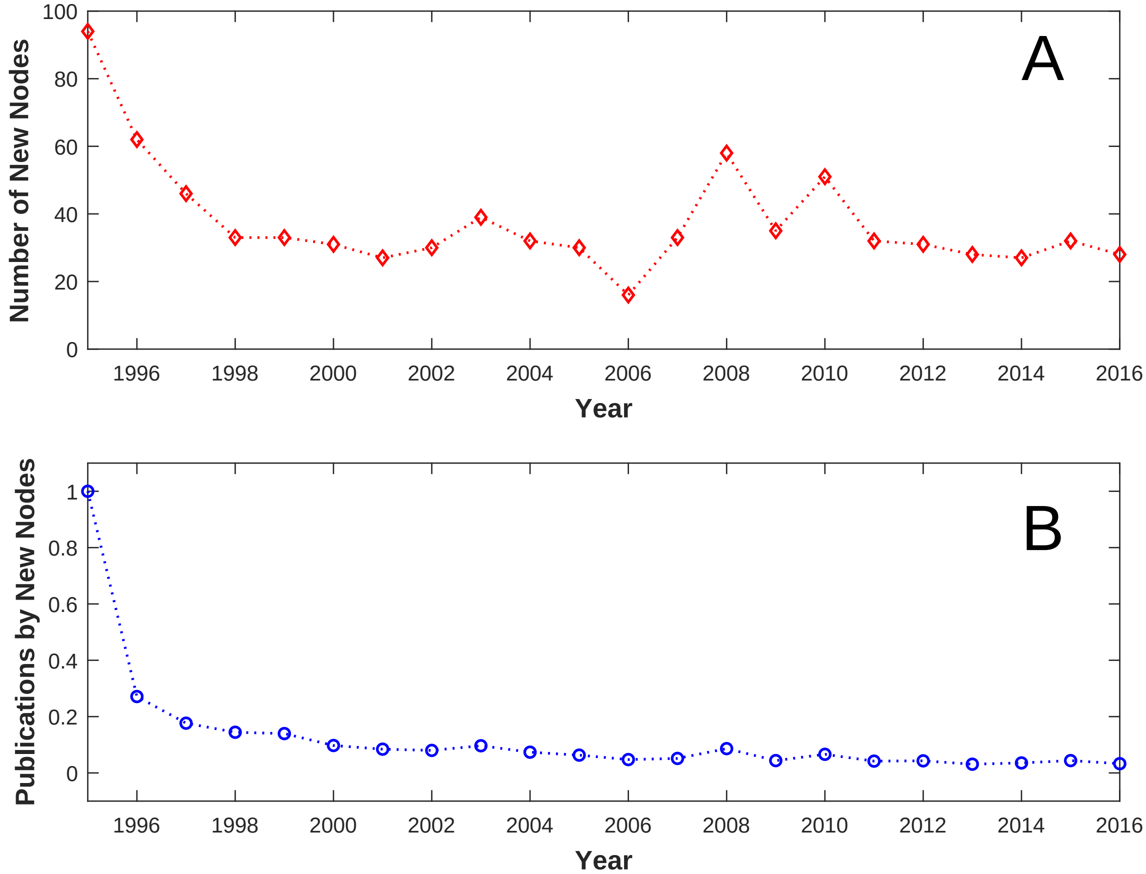

Figure 4. Dynamics of the Collaboration Network. (**A**) The number of newly-joining nodes and (**B**) the proportion of publications by new nodes, for each studied year from 1995 to 2016.

Table 1. Top Finance Journal Publications by Institutions. This table reports the top finance journal publications of the top 50 institutions from 1995 to 2016. The rank is based on aggregate publications across the three journals.

Rank	Institutions	*JF*	*JFE*	*RFS*	All Journals	% of Total
1	NBER	437	347	321	1105	13.30%
2	CEPR	201	142	162	505	6.08%
3	New York University	137	137	119	393	4.73%
4	Harvard University	129	182	71	382	4.60%
5	University of Pennsylvania	125	135	90	350	4.21%
6	University of Chicago	152	97	80	329	3.96%
7	Columbia University	85	77	73	235	2.83%
8	UCLA	70	81	56	207	2.49%
9	Duke University	73	70	58	201	2.42%
10	Stanford University	65	66	56	187	2.25%
11	MIT	72	70	43	185	2.23%
12	University of Michigan	52	59	71	182	2.19%
13	Ohio State University	47	74	60	181	2.18%
14	London Business School	54	51	68	173	2.08%
15	UNC Chapel Hill	49	55	61	165	1.99%
16	University of Texas at Austin	71	46	45	162	1.95%
17	Northwestern University	69	41	49	159	1.91%
18	UC Berkeley	52	49	53	154	1.85%
19	Cornell University	63	39	48	150	1.81%
20	University of Maryland	40	50	49	139	1.67%
21	University of Southern California	38	66	33	137	1.65%
22	UIUC	46	48	37	131	1.58%
23	ECGI	37	27	56	120	1.44%
24	Boston College	34	52	31	117	1.41%
25	Yale University	45	25	43	113	1.36%
26	University of Washington	25	61	24	110	1.32%
27	Washington University in Saint Louis	37	27	42	106	1.28%
28	Indiana University	33	37	32	102	1.23%
29	University of Rochester	28	55	15	98	1.18%
30	HKUST	31	37	25	93	1.12%
31	Federal Reserve Board	39	35	17	91	1.10%
32	Swiss Finance Institute	22	41	28	91	1.10%
33	University of Utah	26	40	25	91	1.10%
34	Arizona State University	28	45	17	90	1.08%
35	INSEAD	18	33	37	88	1.06%

Table 1. - continued

Rank	Institutions	*JF*	*JFE*	*RFS*	All Journals	% of Total
36	LSE	26	14	48	88	1.06%
37	Princeton University	38	33	16	87	1.05%
38	University of Notre Dame	35	37	15	87	1.05%
39	Purdue University	23	42	19	84	1.01%
40	Tilburg University	31	33	18	82	0.99%
41	University of British Columbia	27	20	34	81	0.98%
42	University of Oxford	36	22	23	81	0.98%
43	Emory University	23	38	18	79	0.95%
44	University of Toronto	31	25	23	79	0.95%
45	University of Minnesota	27	26	24	77	0.93%
46	University of Florida	20	39	14	73	0.88%
47	Michigan State University	14	28	30	72	0.87%
48	University of Virginia	24	24	24	72	0.87%
49	Carnegie Mellon University	23	14	34	71	0.85%
50	Federal Reserve Bank of New York	19	24	28	71	0.85%
Total		2927	2916	2463	8306	100%

Table 2. Summary of the 50 Most Prolific Institutions. We categorize the institutions by type, geographic region, and time of establishment.

Type	Universities/Colleges	Research Bureaus/Centers	Banks&Others
Number in Total	45	3	2
Region	North America	Europe	Asia
Number in Total	42	7	1
Establishment	Before 1995	2002	2006
Number in Total	48	1	1

Table 3. Power Law Exponents for Institutions' Top Finance Journal Publications. Estimates are from OLS regressions with standard errors in parentheses.

	All Journals	*JF*	*JFE*	*RFS*
$\widehat{\alpha}$	1.640	1.490	1.689	1.615
	(0.328)	(0.298)	(0.338)	(0.323)
R^2	0.986	0.988	0.982	0.961

Table 4. Power Law Exponents for Institutions' Top Finance Journal Publications over a 5-Year Period. Note the stability in $\widehat{\alpha}$ regardless of increasing mean number of publications.

Year	Mean Number of Publications	$\widehat{\alpha}$	R^2
2015	155	1.632 (0.326)	0.985
2014	146	1.616 (0.323)	0.984
2013	135	1.610 (0.322)	0.980
2012	123	1.572 (0.314)	0.973
2011	113	1.541 (0.308)	0.965

Table 5. Tests of the Power Law Models to Empirical Data. $\widehat{\beta}$ is the Gabaix-Ibragimov statistic with standard errors in parentheses.

	All Journals	*JF*	*JFE*	*RFS*
$\widehat{\beta}$	0.102	0.109	0.182	0.224
	(0.269)	(0.222)	(0.285)	(0.261)

Table 6. Power Law Models by Hill's Tail-Index Estimator. $\widehat{\alpha}^H$ is the Hill's estimator with standard errors is in parentheses. KS-Stat is the Kolmogorov-Smirnov test statistic with p-values is in parentheses.

	All Journals	*JF*	*JFE*	*RFS*
Panel A: Hill's tail-index estimator				
$\widehat{\alpha}^H$	1.489	1.208	1.516	1.313
(s.e.)	(0.205)	(0.166)	(0.208)	(0.180)
Panel B: Kolmogorov-Smirnov test				
KS-Stat	0.065	0.131	0.123	0.124
(p-val.)	(0.968)	(0.300)	(0.373)	(0.357)

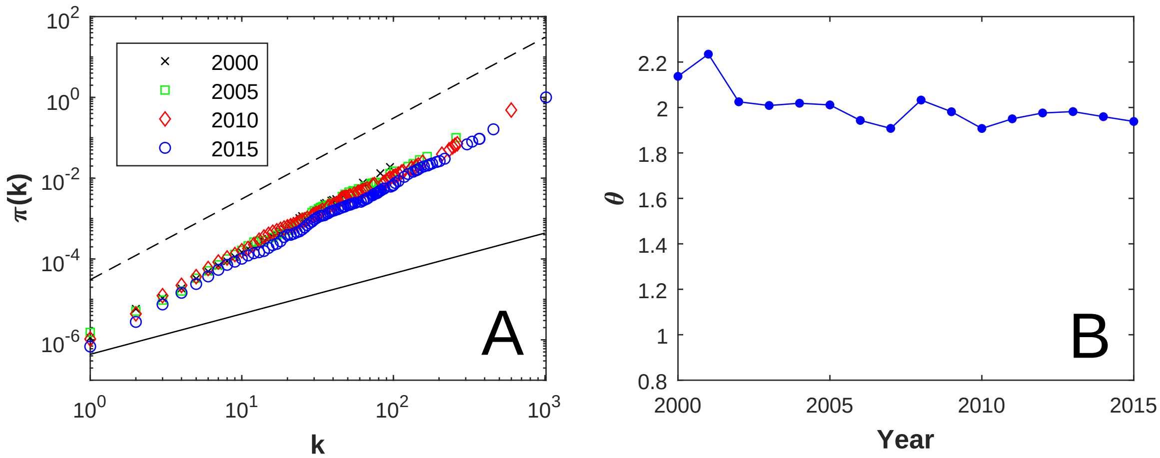

Figure A.1. The $\pi(k)$ Function for the Collaboration Network (A) and the θ Exponent (B). For each curve we used $\Delta t = 1$ *year*. We measure θ for each year from 2000-15 by fitting the whole $\pi(k)$ function. We plot the linear and quadratic $\pi(k)$ functions as the solid and dashed lines in log-log coordinates, respectively.