Mirror, Mirror on the Wall, Who is the Most Central of Them All?

Co-Pierre Georg, and Michael E. Rose

ERSA working paper 571

January 2016

Mirror, Mirror on the Wall, Who is the Most Central of Them All? *

Co-Pierre Georg† and Michael E. Rose‡

In academia, informal collaboration is an integral element in the production of knowledge. We construct the social network of informal collaboration using acknowledgments of 2782 scholarly articles published in six journals in financial economics. We rank financial economists according to their centrality in the network and find that central commenters are not necessarily the most central or the most productive authors. We explore the determinants of high centrality rankings using detailed CV data for the most central academics. A PhD from a better ranked department is associated with a better centrality ranking. Seniority is associated with worse rankings, albeit at a decreasing rate.

Keywords: Knowledge production, formal collaboration, informal collaboration, social network, acknowledgements

* We would like to thank Michael Gofman, Falko Fecht and Alex Oettl for comments and suggestions on an earlier draft. For valuable research assistance, we thank Francis Leni Anguyano, Patricia Chirwa, Aldu Duminy, Samantha Filby, Jesslyn Jonathan, Chris McPetrie and Khanyisa Yolanda Nogaya. We also thank Martin Rünz and Claudio Rocchini for their code used for a graph.

† University of Cape Town. E-Mail: co-pierre.georg@uct.ac.za, Economic Research Southern Africa, and Deutsche Bundesbank. The views expressed in this paper do not necessarily reflect the views of Deutsche Bundesbank.

‡ University of Cape Town. E-Mail: rsxmic005@uct.ac.za. Corresponding author.

JEL Classification: A14, D83, G00

1. Introduction

Collaboration is increasingly important for scientific progress. Academics collaborate formally by co-authoring research papers, but most collaboration is informal, e.g. providing commentary to colleagues, feedback during seminar presentations, giving discussions at conferences, or refereeing manuscripts for scholarly journals. With few notable exceptions, however, the literature studies formal collaboration only. We study the social network of informal collaboration in financial economics, rank the most central financial economists in our network, and investigate their characteristics.

Editors of the top scholarly journals in financial economics advise authors to collaborate informally (Green et al., 2002) and young economists are encouraged to acknowledge helpful input generously (Thomson, 1999). Indeed, authors commonly acknowledge helpful colleagues, seminar and conference participants as well as referees in the title page footnote or a separate section (Laband and Tollison, 2000; Cronin, 1995). We use this unique setting in which informal collaboration is well documented, to construct a novel dataset on informal collaboration.

We distinguish between three forms of informal collaboration.[1] First, *social* informal collaboration is the collaboration between authors and commenters who are individually acknowledged for providing commentary, insights or for engaging in discussions about the paper. Second, *institutional* informal collaboration captures presentations in research seminars at universities, central banks, government institutions, and think tanks. And third, *institutionalized* informal collaboration captures conferences where a paper has been presented. While all three forms increase over time at the extensive and intensive margin, their differences reveal journal-specific patterns.

In this paper we focus on social informal collaboration only and construct a net-

[1]The term derives partly from Laband and Tollison (2000, pp. 645-646), who refer to the provision of commentary by colleagues as informal intellectual collaboration.

work which we term social network of informal collaboration. Networks are a necessary conduit for information transmission and as such, they enjoy growing attention of scientists to highlight the flow of information (Phelps et al., 2012). The social network of informal collaboration connects financial economists whenever one acknowledges the other. However, information also flows among co-authors. We therefore add a link between two researchers if they co-author a paper.

Different network centrality measures shed light on the role specific individuals play in the transmission of information or the influence they exert on their neighbors Jackson (2014); Ballester et al. (2006). We rank the most central financial economists according to two different centrality measures obtained from the social network of informal collaboration and compare their rank with centrality measures obtained from the social network of formal collaboration (i.e. the network of co-authorship). These centrality measures are betweenness centrality and eigenvector centrality, both of which are related but distinct: betweenness centrality measures the importance for transmitting information while eigenvector centrality points to the most connected group, i.e. the opinion leaders, in the network.

To understand what determines network centrality, we conduct ordered logit regressions on subsets compromising the 100 most central financial economists in the social network of informal collaboration. The subsets are distinct because a researcher with high betweenness centrality is not necessarily highly eigenvector central. Results from the regressions suggest that seniority is most important for a high eigenvector centrality. Having served many years as editor in multiple journals is associated with a high betweenness centrality rank.

Studying informal collaboration yields insights in the process of knowledge generation over and above what one can learn from formal collaboration.[2] By restricting themselves to co-authorship linkages, studies of the flow of information embedded

[2]The rich literature on co-author networks expands to questions as how co-author links emerge (McDowell and Melvin, 1983; Freeman and Huang, 2015), what the individual benefits of network links to authors are (Azoulay et al., 2010; Ductor et al., 2014) and whether teams are more productive than solo-authors (Wuchty et al., 2007).

in co-authorship networks might overestimate the importance of highly productive individuals. Goyal et al. (2006), for example, show that the network of formal collaboration evolves into a network with small-world properties as technology lowers the cost of formal collaboration, i.e. makes it easier to co-author papers. Including connections between authors and commenters allows us to analyze various dimensions of information flow. For instance, most authors are isolated in the social network of formal collaboration but end up well connected once we include author-commenter links. Our paper thus provides a more nuanced view of the generation of knowledge which can help identifying the determinants of successful research papers.

Our results are not only relevant to other financial economists working in the field. We also provide the first large-scale examinations of the social network of informal collaboration in science, which is visible only through acknowledgements. From this perspective, Economics is an interesting discipline because it strongly emphasizes informal collaboration, compared to the natural sciences (Laband and Tollison, 2000). Additionally, it is more hierarchically organized and less fragmented than other social sciences (Fourcade et al., 2015). Financial economics itself is an interesting field because it is both sufficiently large and homogeneous.

2. Data

We use data from two different sources: 1) Acknowledgment sections and bibliometric data from 2782 research articles and 2) CVs of 258 financial economists.

Our main data source is research articles that have been published in six scholarly journals. We focus on six journals with a similar focus on financial economics: The Journal of Finance (JF), the Journal of Financial Economics (JFE), The Review of Economic Studies (RFS), the Journal of Financial Intermediation (JFI), the Journal of Money, Credit, & Banking (JMCB), and the Journal of Banking and Finance (JBF). The first three journals are commonly regarded as general interest journals, while the remaining three journals are considered to be field journals. The set of general interest journals for example is identical to the set used in the study of Borokhovich et al. (2000), who examine impact in financial economics. As of 2014, all general interest journals had an impact factor well above five, while the field journals' impact factor was between 1.5 and 2.5.

We look at articles published during two sample periods: The *early* sample consists of articles published between 1998 - 2000 and the *late* sample of those published between 2009 - 2011. The rationale behind this split is to account for effects of organizational and technological change on the academic publication process. We restrict our analysis to what the publishers Wiley (JF and JMCB), Oxford Journals (RFS) and Ohio State University Press (JMCB) call Articles and what Elsevier (JBF, JFE, JFI) calls Original Research Articles. Additionally, we omit notes, discussions, shorter articles, conference announcements, minutes, policymakers roundtable, etc. This gives us a total of 2782 (early: 887; late: 1895) articles.

The sample is very homogeneous: 92% of 2261 articles listing Journal of Economic Literature (JEL) codes belong to JEL category G (Financial Economics).[3] Additional 6% list E (Macroeconomics and Monetary Economics), but not G. The six journals are not only homogeneous in their research focus, but also in their editorial process: All journals except the JMCB used single blind referee process throughout the sample period, which puts the JMCB at a mildly special position. The JFE used to be special as well, as it had a policy according which referees could reveal themselves upon publication. On top of that, three journals (RFS, JFE and JBF) explicitly encourage authors to acknowledge helpful individuals on the paper.[4]

For each paper we collect standard bibliometric information. This includes title, all authors, each affiliation for all authors, listed JEL codes and the number of pages.

Our main interest is directed at acknowledgement sections, typically located on

[3] Not all articles list JEL codes. The JF for instance never lists JEL codes, while the RFS introduced JEL codes in Winter 2006 only. For articles not listing JEL codes, we conducted an internet search to obtain JEL codes from latest working paper version. This is the case for 224 articles.

[4] We are grateful to the journal editors for answering a short questionnaire.

the title page of an article. Authors commonly acknowledge helpful input by colleagues and state where a paper has been presented. Funding sources and hospitality during visiting positions are often acknowledged, too, as well as research assistance. From the acknowledgement section we collect: which seminars and conferences the article has been presented, visiting (and former) faculty positions and the names of colleagues that have provided input.

Cronin (1995) distinguishes three general forms of acknowledgements, namely resource-related (funding, data and materials), procedure-related (editorial and moral support) and concept-related (ideas, feedback and commentary). We focus on concept-related acknowledgements only, and within this category we distinguish the following groups of acknowledged individuals: (1) editors, (2) referees, (3) discussants, (4) PhD advisers and committee members, (5) colleagues that have provided comments (commenters), (6) colleagues that have provided data, (7) research assistants, and (8) non-academic personnel from banks and industry. In what follows we restrict our analysis to categories (3) to (5). There are several reasons for our focus. First, there is no flow of academic information involved in categories (6) to (8). Second, the vast majority of articles acknowledges the editor of the respective journal. If we calculate an editor's structural embeddedness, we are likely to be biased towards frequently publishing journals. The more articles a journal publishes, the better is its editor's perceived centrality in the data. By excluding editors from our sample during their tenure, we avoid this issue. The same is true for referees, but they are rarely known by name.[5]

A consolidation procedure is necessary because the same name is frequently spelled in different ways. The Journal of Finance's longtime editor Campbell R. Harvey is being acknowledged as Cam Harvey, Campbell Harvey, Campbell R. Harvey, and Campell Harvey (with a typo). An additional problem arises for example

[5]Due to the Journal of Financial Economics' journal policy, referees may choose to reveal themselves upon publication. Authors then acknowledge the referee. Other journals don't list referees by name.

with different naming conventions e.g. for Asian names (first name, last name vs. last name, first name). To account for all these effects, we conduct an internet search for all authors and acknowledged individuals to find their full and proper name. After the consolidation process we are left with 3449 (7522) names in the early (late) timeframe. Some researchers appear in both timeframes, which gives us a total of 9463 academics in our dataset.

The vast majority of published research articles acknowledges informal input by colleagues. Of all the 2782 articles in our dataset, 501 (18%) articles do not acknowledge any commenter.[6] In total, the share of articles reporting informal collaboration (the extensive margin) has remained very stable over time, albeit general interest publications report informal collaboration more often. Figure 1 documents this development.

FIGURE 1 ABOUT HERE

General interest publications not only acknowledge informal collaboration more often, they also report a higher intensity of informal collaboration. Figure 2 shows the average number of authors, commenters, seminars and conferences, grouped by year and journal. General interest publications acknowledge almost twice as many colleagues than papers published in a field journal (left figure), and are presented more than twice as often at seminars and conferences (center and right figure).

FIGURE 2 ABOUT HERE

Another striking fact is how well the general journal ranking is reflected by the amount of informal collaboration. The Journal of Finance (JF) usually has the highest intensity of informal collaboration, with the Journal of Banking and Finance mostly at the bottom. All three general interest journals are very close together. But not so the

[6]These articles may, however, acknowledge comments by editors, referees, funding, data exchange and research assistance. We are only interested in informal collaboration prior to publication.

field journals, where collaboration patterns in the Journal of Financial Intermediation resemble those in general interest journal more and more.

After looking at mean aggregations by journal, we take a closer look at the distribution per journal category. Figure 3 is a combined violin-boxplot comparing the distribution of the number of all acknowledged individuals for the early sub-sample (1998-2000) and the late sub-sample (2009-2011). For each sample, the plot shows the distribution of acknowledged commenters per journal category, that is for all general interest journals and all field journals distinctively. Inside the violinplot is a boxplot highlighting all quintiles and outliers.

FIGURE 3 ABOUT HERE

General interest journals have at all times acknowledged more individuals and the bandwidth is increasing: The record for the number of commenters is held by Spamann and Holger (2010): 'The "Antidirector Rights Index" Revisited', *The Review of Financial Studies* **23**(2), 467-486, which acknowledges as many as 53 persons. Both groups of journals are diverging over time, as the spread between the median values increases.

Our second data source are CVs of the most central researchers. We restrict our analysis to the 100 most betweenness central and the 100 most eigenvector central individuals in both samples. All CVs are publicly available on the websites of the researchers.[7] We combine the data with the Tilburg University Economics ranking of 2013.[8] It ranks 944 Universities and research institutes worldwide according their unweighted publication output in 70 journals during the previous five years.[9] Authors from higher ranked universities might have more publication success for two reasons: First, editors and other might see an author's affiliation as a signal of strength of

[7]All data were downloaded in 2015.

[8]Data downloaded on 7 March 2014.

[9]By using the Tilburg ranking we underestimate the ranking of authors affiliated with a central bank or business school. Given the large sample size we have, this error will be small, however. As of yet, there is no research ranking of central banks available.

the author and thus of the paper. As a consequence, an article might be more visible. Second, authors from better ranked universities have colleagues who have more publication success and are thus able to provide more insightful feedback.

Using information from CVs, we compute seven variables: 1) the rank of the PhD granting university in the 2013 Tilburg Ranking, 2) the Tilburg rank of the current affiliation, 3) a binary variable equal to 1 if the researcher is a woman,[10] 4) the number of years the person has been serving as managing or associated editor, 5) a binary variable indicating membership in either NBER or CEPR as of 2015, 6) seniority, measured as the difference between the year 2012, the last year in our data sample, and the year in which the PhD was awarded, and 7) the square of seniority to capture non-monotonic age-effects. The eighth variable is the number of times a person has been acknowledged during the current dataset (early or late) and is obtained from our main dataset.

3. Two social networks

Using bibliometric and acknowledgement information, we construct two types of social networks. In the social network of formal collaboration (or network of co-authorship) academics are connected by an undirected and weighted link whenever they have co-authored a paper. Links between two academics are weighted with the number of joint papers. Kenneth R. French and Eugene F. Fama, for instance, have 5 joint papers in our dataset.

While co-authorship, which is a formal and strong form of collaboration, is relatively rare in our sample, informal collaboration in the form of feedback on a manuscript is relatively common. The network of informal collaboration adds undirected and weighted links to the network of formal collaboration. A new tie is recorded whenever one academic acknowledges the other. The tie is undirected, because infor-

[10]We determine whether a researcher is a woman based on the website, e.g. writing "him" or "her".

mation flows in both directions: from the author to the commenter because the author tells the commenter, sometimes in great detail, about the paper, and from the commenter to the author, because the commenter provides feedback. Each link between an author and an acknowledged commenter is weighted with the inverse number of authors to account for the fact that commenters typically provide feedback to a single author. The strongest link has a weight of 8 and is between Amir Sufi and Douglas W. Diamond.

Consequently, every author shows up in both networks: in the network of formal collaboration with her co-authors as network neighbors, and in the network of informal collaboration with her co-authors and her acknowledged commenters as neighbors.

Both networks account for different dimensions of scientific collaboration. A node with many ties in the *formal* network (co-author network) is someone who is likely to publish and collaborate often. Therefore, the formal network captures productivity. The network of *informal* collaboration on the other hand additionally accounts for information embedded in less formal but common interactions between academics. Studies on co-authors networks hence underestimate the information flow embedded in the informal exchange of ideas and information between authors and commenters.

The network of informal collaboration additionally captures a dimension that Oettl (2012) denotes helpfulness. This is plausible because a node with many ties in the network of informal collaboration represents a researcher that comments (discusses, advises, etc.) often. A very productive researcher is not necessarily a very helpful researcher in the sense that she helps others during the publication process.

The rise of co-authorship in scientific work has been well documented (McDowell and Melvin, 1983; Barnett et al., 1988; Goyal et al., 2006). A crucial assumption of these studies is that information flows through joint papers and projects. This literature, however, is oblivious to other forms of information flow between academics. The connectedness of authors increases dramatically when commenters are taken into account. Table 1 gives an overview of key figures of the social network of formal collaboration while Table 2 shows key figures for the social network of informal collaboration. To highlight existing differences between the journals, we also build networks using subsamples of general interest journals and field journals.

TABLE 1 ABOUT HERE

TABLE 2 ABOUT HERE

Due to the higher number of co-author links, the network is more connected in 2009-2011 than it was a decade earlier. For example, the number of unconnected components decreased while the size of the giant component increased. This is also visible in Figure 4, which shows the co-author network for both points in time.

FIGURE 4 ABOUT HERE

Comparing the two subsamples by journal quality provides evidence that in all dimensions the formal network for general interest journals is better connected than the network build of field journal publications only. While there were more authors publishing in general interest than in field journals in the early sample, the reverse is the case for the late sample: the number of authors publishing in general interest journals has doubled from the late to the early sample, but at the same time the number of authors publishing in field journals has more than tripled. The rise in co-authorship documented in the literature can be seen in the increase in the number of edges (each edge indicating a unique co-author relationship). There are more than twice as many edges for publications in general interest journals in the late sample than in the early sample and over four times as many in the field journal sample. The expansion of the network from the early to the late sample did not lead to an increase of the shortest path length within the network, which is relevant for the transmission of information.

Direct comparison of both social networks highlights the estimation error when informal social collaboration is ignored: There are at least twice as many nodes and at least ten times as many edges. The contrast is even starker for general interest publications. The overlap between the two social networks is surprisingly small: Out of 3919 authors, 1858 (about 47%) are never acknowledged as commenter. Of 7603 acknowledged researchers 5542 (about 72%) are not publishing in the set of our journals. These relationships hold for every subset, regardless of journal quality, or early or late sample. Obviously, a lot more researchers are involved in the generation of knowledge than those actually publishing.

Table 2 gives an idea of the connectedness of the social network of informal collaboration, too. The network expanded massively due to the larger number of commenters. The expansion is proportionally larger than the increase in the number of publication would suggest. Although the number of edges grew more than the number of nodes, the network has not become more connected generally. The number of components increased, entirely caused by publications in field journals. The largest component – the so called giant component – was already very large in the early subsample, connecting more than 95% of all academics in the network, and has grown even more to 98%. Density remained at values close to 0 and the average shortest path length remained broadly constant at 4.5. Diameter, being the longest of all shortest paths, even increased by two nodes, meaning that information today travels longer on average through the social network of informal collaboration.

Figure 5 shows the social network of informal collaboration for both points in time. The links are color-coded according journal group, with links occurring in field journals being blue and those in general interest journal being red (links occurring in both points in time are extremely rare and colored in purple). It is a striking feature of both timeframes that blue links are almost exclusively at the network's periphery while the remaining red links dominate the center. This highlights the importance of central commenters for the flow of information traversing from one side of the network to the other.

FIGURE 5 ABOUT HERE

The observation that commenting on each others work is prevalent raises the question as to why researchers invest their sparse time to read manuscripts when they do not receive credit for it. One possible explanation is that researchers are following a quid-pro-quo strategy, that is to help colleagues that have helped them. Our data allow us to calculate the amount of reciprocity in the social network of informal collaboration. Reciprocity takes two forms: First, comment on the work of one's coauthors, and second, comment on the work of one's commenters.

We first examine whether acknowledged commenters are also co-authors. We denote the number by Θ and define it for each timepoint $t \in \{\text{early, late}\}$ as the sum of all commenter-author links that appear both in the social network of formal collaboration G^a and the social network of informal collaboration G^c:

$$\Theta_t = \sum_p^P \sum_I^{\kappa_p} \sum_F^{\iota_p} \{g_{ik}^I | g_{ik}^I = g_{ik}^F = 1\}. \tag{1}$$

$g_{ik}^I = 1$ if commenter i is acknowledged by author k, while $g_{ik}^F = 1$ if i and k have coauthored a paper. Θ_{early} is 193, while Θ_{late} equals 538. In order to normalize these numbers, we divide by the number of possible links Ξ. We define Ξ_t for each t as:

$$\Xi_t = \sum_p^P \sum_k^{\kappa_p} \mathcal{N}_{ak,t}(G^F) \setminus \kappa_p, \tag{2}$$

where $\mathcal{N}_{k,t}(G^F)$ is the set of neighbors of author k in the network of formal collaboration G^F in timepoint t. In the early (late) sub-sample there are 1180 (4664) possible links of commenting co-authors. Hence, between 1998 and 2000, $(\Theta_{\text{early}}/\Xi_{\text{early}}) * 100\% \approx 16\%$ of all (feasible) authors commented on their co-authors other work, while between 2009 and 2011 the respective ratio decreased to $\Theta_{\text{late}}/\Xi_{\text{late}} * 100\% \approx 12\%$. It remains subject to speculation why over time less authors read the drafts of their co-authors.

Next, we examine the extend to which authors comment on the work of their commenters. We define the number of reciprocal commenter links as Λ_t for each timepoint t, where

$$\Lambda_t = \sum_{i}^{N^I} \sum_{j \neq i}^{N^I} \{g_{ij}^I | g_{ji}^I = 1\} \tag{3}$$

for any two nodes i and j in the social network of informal collaboration. The count of reciprocal links in the early sub-sample equals 698 and 1364 in the late sub-sample. In order to normalize these numbers, we divide by the number of possible reciprocal links ϕ. There are two necessary conditions for a possibly reciprocal commenter link: First, j is an author herself, that is $j \in N^F$, and second, there is at least one paper where j is not a coauthor of i, that is $j \notin \mathcal{N}_i(G^F)$. Hence,

$$\phi = \sum_{i}^{N^I} \sum_{j \neq i \wedge \in N^F \wedge j \notin \mathcal{N}_i(G^F)}^{N^I} g_{ji}^I \tag{4}$$

In the early sub-sample there are 2912 such links, while in the late sub-sample there are 8117 links that could possible be reciprocal. Hence, $\Lambda_{\text{early}}/\phi\text{late} * 100\% \approx 24\%$ and $\Lambda_{\text{late}}/\phi\text{early} * 100\% \approx 17\%$. Again, it is a puzzle while the share of reciprocal author-commenter links declined.

One caveat is in order, as we only observe commenting ties within our dataset consisting of financial economics journals. This is not necessarily the natural domain of all commenters, given their field of expertise. For example, 2014's Nobel price laureate Lars Peter Hansen has been acknowledged by more than 20 articles in our dataset, while he didn't author a single article in our dataset.

4. Who are the most central authors and commenters?

While the previous section examines the global structure of the social network of formal and informal collaboration, we now turn to a closer analysis of individual academics. For every node in S^F as well as for every node in S^I we compute the degree. For nodes that are in the respective giant components we additionally compute betweenness centrality and eigenvector centrality. We also count, in our dataset, the number of papers an author wrote and the number of times a commenter is acknowledged. The number of published papers can be understood as measure of productivity while the number of times a commenter is being acknowledged serves as helpfulness measure (Oettl, 2012).

We compute Spearman correlation coefficients among all centrality measures in both networks. We also correlate the measures with the number of papers per author and the number of times the person has been acknowledged. Table 3 shows the correlation coefficients for both timepoints (early networks in Panel A, late networks in Panel B).

TABLE 3 ABOUT HERE

There are three interesting facts we want to highlight: First, being an author with a high number of papers is positively, but not strongly correlated with being a central author - except for betweenness centrality. Second, being an author with a high number of published papers is only mildly correlated with being a frequently acknowledged commenter (correlation is 0.33 in the early and 0.35 in the late time-frame). Third, and most interestingly, central commenters are usually not central authors–the highest correlation is 0.63, and between betweenness central commenters are usually not betweenness central authors.

The low correlation between productive and central commenters suggests limited scope for strategic acknowledging, by which authors try to steer editors.[11] For example, authors would mention well-known researchers in the field to signal quality. Another possibility is to acknowledge peers having a reputation of being demanding referees to prevent the editor picking the already acknowledged peer as referee to the

[11] Hamermesh (1991) defines strategic acknowledging as thanking "someone who has not seen the paper, as a talisman against that person being chosen" as referee. He continues to write "DON'T PLAY THESE GAMES" (p. 171) [Emphasis in the original]. Editors however suggested to us that they rarely look into the acknowledgements, and if so, to pick a referee.

paper. A third possibility is to acknowledge researchers that are socially close to the editor, again as a signal to the editor (and the referee, in case of single-blind referee processes). From our data it is visible, that it is precisely not the most productive authors that are being acknowledged often.

To make our analysis more palpable, we list the 25 most central authors according our two centrality definitions along with the 25 authors with the highest degree and the 25 authors with the most papers in our dataset. Table 4 lists the authors from the early timeframe while table 5 lists those for the late timeframe.[12]

TABLE 4 ABOUT HERE

TABLE 5 ABOUT HERE

Laband and Tollison (2003) compile a list of the most often thanked authors from a sample of three general interest Economics journals over forty years. Our sample however adopts a network view of a much more homogeneous sample. Table 6 lists 25 top nodes in terms of a) degree, b) betweenness centrality, c) eigenvector centrality and d) number of thanks in the early timeframe (1998-2000). Table 7 does so for the late timeframe (2009-2011).

TABLE 6 ABOUT HERE

TABLE 7 ABOUT HERE

Some of the great financial economists of our time are prominently featured in the ranking. Again, it is apparent that often thanked scientists are not necessarily those most central e.g. in terms of betweenness centrality.

It is worth noting that the rankings are only partially overlapping. For example, of the 25 most thanked commenters in the late social network of informal collaboration, only 11 are among the 25 researchers with the highest degree, nine are among the 25 most betweenness central researchers and ten are among the 25 most eigenvector central researchers.

[12] In the Online Appendix B we list the top 100 most central academics.

5. What determines centrality rank?

It is not only interesting to know the names of the most central researchers, but also what they have in common. To this end, we explore the determinants of the 100 most central financial economists in the social network of informal collaboration.

We explore the determinants of the rankings of two partially overlapping subsets for each point in time: From the 100 most betweenness central researchers in the late subset, only 35 are among the 100 most eigenvector central individuals and vice versa. In the early subset there are 40 individuals that are both among the 100 most betweenness central researchers and the 100 most eigenvector central researchers. For this reason we report two distinct summary statistics per point in time. Table 8 presents the summary statistics for the early subset (1998-2000) and Table 10 those for the late subset (2009-2011). All the characteristics but the last originate from the author's CV, which we obtain by conducting an internet search. The first column, N, indicates the number of persons for which the corresponding observation is available. For example, not every CV is available, not every affiliation is ranked in the Tilburg Economics University ranking, not every researcher indicated the year in which he obtained his PhD in his CV, and so on.

Looking at the average top 100 researchers reveals some interesting insights on who is acknowledged and who maintains a central position in the network. Table 10 presents summary statistics of individual characteristics for the 100 most often acknowledged researchers (Panel A), the 100 most betweenness central researcher (Panel B), and the 100 most eigenvector central researchers (Panel C). The average top 100 most often acknowledged commenter has been trained at fairly high ranked universities, works now at a much lower ranked university, is male (there are four women in the ranking), has served nearly 13 journal-years as editor (each year per journal counts as one year), is a member of either NBER or CEPR in half of the cases, has received the PhD about 24 years ago and has been acknowledged 25 times. In comparison, the average top 100 betweenness central researcher has been trained at a lower ranked university. Both the average top 100 betweenness central researcher and the average top 100 eigenvector central commenter work at higher ranked universities, are less often member of either NBER or CEPR, less senior and less often acknowledged. There are differences among the most central commenters, too: the average top 100 betweenness central commenters has been acknowledged less often, is more senior and has served more years as editor than the average top 100 eigenvector central commenter.

Table 8 ABOUT HERE

Table 10 ABOUT HERE

In contrast, Table 8 shows that all average top 100 individuals were much more similar in the early subset. On average, all groups graduated from universities that are ranked similarly, work at relatively equally ranked universities today, are male, have worked 12.5 to 15 years as editor in total, are a member of NBER or CEPR in every fourth case and look back on 26 to 28 years of experience. They have been acknowledged on average about 10 times in the early subset.

We fit the following proportional odds model to study which characteristics explain a good placement in our rankings:

$$\text{logit}(p(Y \leq g)) = \beta_{0_g} - (\beta_1 X_1 + \ldots + \beta_8 X_8) \quad (g = 1, \ldots, 99) \tag{5}$$

where $X_1, \ldots, X_8$ correspond to the eight variables described above. The corresponding coefficients $\beta_1, \ldots, \beta_8$ are proportional odds ratios and apply at the sample mean. Their interpretations are similar to those of common logistic regressions: Increasing the explanatory variable by 1 unit, the odds of being ranked 50 applying versus being ranked lower are x times greater, where x is the coefficient.

Table 9 reports regression results for the early subset, while Table 11 reports those for the late subset. In the first column, Y is the rank according the number of acknowledgments, in the second column Y is the betweenness centrality rank and in the third column Y is the rank according eigenvector centrality. Hence, a negative coefficient would be associated with a higher rank.

Turning to the early subset (Table 9) first, the rank of the PhD institution as well as the rank of the current affiliation have no statistically significantly effect on the ranking, regardless of the dimension. There is weak evidence that female researchers are higher ranked in the acknowledgment- and the betweenness centrality ranking but lower ranked in the eigenvector centrality ranking. Having served many years as editor is insignificantly associated with a high rank, except for betweenness centrality. Being member of either NBER or CEPR is associated with a more central position, but also with being acknowledged less often. There are decreasing negative seniority effects for the rank eigenvector centrality.

Table 9 ABOUT HERE

Table 11 ABOUT HERE

In the late subset (Table 11), the ranking of the PhD affiliation is now positively associated with a high rank, while women now experience a statistically insignificant malus on all rankings. Having served many years as editor, however, is associated with a lower acknowledgement-ranking. Being a member of either the NBER or CEPR is associated with lower ranks in all specifications (the coefficient in the thanks ranking is the only one being statistically significant, though). Non-trivial seniority effects pertain in the late subset as well: The older a researcher becomes, the lower his ranking according the number of thanks and eigenvector centrality until a tipping point, after which ranks improve with age. The relationship for betweenness centrality is the opposite, but with high standard deviations.

6. Concluding remarks

This paper highlights the importance of informal collaboration in our profession. Informal collaboration is, in different shades, vital to other disciplines as well (Cronin, 1995). The investigation of informal collaboration, as well as the flow of information they reveal, can help to understand differences in (perceived) quality among journals, research papers and authors. They have implications for researchers, especially junior ones, as they suggest to informally collaborate from the very first step of the career.

We document the structure of the social network of informal collaboration and its evolution over time. There is a substantial difference between the social network of formal collaboration, i.e. co-authorship, and the social network of informal collaboration. Focusing on co-authorship networks will therefore likely ignore important channels of information transmission.

The next natural question to ask is whether receiving commentary from a colleague increases the subsequent publication success of a research paper if the colleague is more central in the social network of informal collaboration. One shortcoming of our data is that the Tilburg ranking of universities does not include central banks and other policy institutions but which engage in high-quality academic research. A better suited ranking would include these institutions. Another closely related question is in how far an adviser's position in the social network of informal collaboration affects the placement of PhD students. A vast literature on job referrals in labor economics (see, for example, Kramarz and Skans (2014)) suggests such a relation. Finally, Welch (2014) shows that referee recommendations differ significantly for the same paper. It would be interesting to study whether social distance of a referee to the author plays a role in the recommendation. Brogaard et al. (2014) show that having an editor of a journal as visiting faculty increases the probability that papers of other faculty members are published in the editor's journal. But these papers receive more than average citations, which motivates the hypothesis that additional information (i.e. lower social distance) to an author would allow referee's to make better informed decisions about the paper's *"true"* quality.

All these questions are relevant to the profession and our paper is merely a first step towards a broader understanding of the role informal collaboration plays in the creation of knowledge.

References

Azoulay, P., Graff Zivin, J. S. and Wang, J. (2010), 'Superstar Extinction', *The Quarterly Journal of Economics* **125**(2), 549–589.

Ballester, C., Calvó-Armengol, A. and Zenou, Y. (2006), 'Who's Who in Networks. Wanted: The Key Player', *Econometrica* **74**(5), 1403–1417.

Barnett, A. H., Ault, R. W. and Kaserman, D. L. (1988), 'The Rising Incidence of Co-authorship in Economics: Further Evidence', *The Review of Economics and Statistics* **70**(3), 539–43.

Bonacich, P. (1986), 'Power and Centrality: A Family of Measures', *American Journal of Sociology* **92**(5), 1170–1182.

Borokhovich, K. A., Bricker, R. J. and Simkins, B. J. (2000), 'An Analysis of Finance Journal Impact Factors', *The Journal of Finance* **55**(3), 1457–1469.

Brogaard, J., Engelberg, J. and Parsons, C. A. (2014), 'Networks and productivity: Causal evidence from editor rotations', *Journal of Financial Economics* **111**(1), 251–270.

Cronin, B. (1995), *The Scholar's Courtesy: The Role of Acknowledgment in the Primary Communication Process*, Taylor Graham, Los Angeles, CA.

Ductor, L., Fafchamps, M., Goyal, S. and Leij, M. J. V. D. (2014), 'Social Networks and Research Output', *The Review of Economics and Statistics* **96**(5), 936–948.

Fourcade, M., Ollion, E. and Algan, Y. (2015), 'The Superiority of Economists', *Journal of Economic Perspectives* **29**(1), 89–114.

Freeman, L. C. (1979), 'Centrality in Social Networks Conceptual Clarification', *Social Networks* **1**, 215–239.

Freeman, R. B. and Huang, W. (2015), 'Collaborating with People Like Me: Ethnic Co-authorship within the US', *Journal of Labor Economics* **33**(S1), S289–S318.

Goyal, S., van der Leij, M. J. and Maria-Gozalez, J. L. (2006), 'Economics: An Emerging Small World', *Journal of Political Economy* **114**, 403–412.

Green, R., O'Hara, M. and Schwert, G. W. (2002), 'Joint editorial', *The Journal of Finance* **57**(2), 1031–1032.

Hamermesh, D. S. (1991), 'The Young Economist's Guide to Professional Etiquette', *The Journal of Economic Perspectives* **6**(1), 169–179.

Jackson, M. O. (2014), 'Networks in the Understanding of Economic Behaviors', *Journal of Economic Perspectives* **28**(4), 3–22.

Kramarz, F. and Skans, O. N. (2014), 'When Strong Ties are Strong: Networks and Youth Labour Market Entry', *The Review of Economic Studies* **81**(3).

Laband, D. N. and Tollison, R. D. (2000), 'Intellectual Collaboration', *Journal of Political Economy* **108**(3), 632–661.

Laband, D. N. and Tollison, R. D. (2003), 'Good colleagues', *Journal of Economic Behavior & Organization* **52**(4), 505–512.

McDowell, J. M. and Melvin, M. (1983), 'The Determinants of Co-Authorship: An Analysis of the Economics Literature', *The Review of Economics and Statistics* **65**(1), 155–160.

Oettl, A. (2012), 'Reconceptualizing Stars: Scientist Helpfulness and Peer Performance', *Management Science* **58**(6), 1122–1140.

Phelps, C., Heidl, R. and Wadhwa, A. (2012), 'Knowledge, Networks, and Knowledge Networks: A Review and Research Agenda', *Journal of Management* **38**(4), 1115–1166.

Thomson, W. (1999), 'The Young Person's Guide to Writing Economic Theory', *Journal of Economic Literature* **37**(1), 157–183.

Welch, I. (2014), 'Referee Recommendations', *The Review of Financial Studies* **27**(9), 2773–2804.

Wuchty, S., Jones, B. F. and Uzzi, B. (2007), 'The Increasing Dominance of Teams in Production of Knowledge', *Science* **316**(5827), 1036–1039.

A. Appendix

A.1. Tables

Table 1: Global network measures for the social network of formal collaboration

temp	**Early (1998-200)**			**Late (2009-2011)**		
	All	General interest	Field	All	General interest	Field
Nodes	1265.00	722.00	618.00	3109.00	1423.00	1864.00
Edges	1025.00	622.00	420.00	3229.00	1666.00	1597.00
Components	502.00	264.00	299.00	903.00	310.00	730.00
Giant component	53.00	27.00	20.00	601.00	398.00	45.00
Density	0.06	0.11	0.16	0.01	0.01	0.06
Avg. path length	5.16	4.37	2.66	10.76	10.10	4.31
Diameter	13.00	10.00	5.00	27.00	24.00	9.00

Note: General interest contains only the general interest journals JF, JFE, and RFS. *Field* contains the field journals JFI, JMCB, and JBF. The variables "Avg. path length" and "Diameter" were calculated using the giant component only.

Table 2: Global network measures for the social network of informal collaboration

temp	**Early (1998-200)**			**Late (2009-2011)**		
	All	General interest	Field	All	General interest	Field
Nodes	3457.00	2256.00	1658.00	7573.00	4387.00	4515.00
Edges	11829.00	8739.00	3200.00	35495.00	25243.00	10594.00
Components	75.00	14.00	96.00	171.00	7.00	228.00
Giant component	3188.00	2217.00	1225.00	7056.00	4366.00	3726.00
Density	0.00	0.00	0.00	0.00	0.00	0.00
Avg. path length	4.59	4.04	5.84	4.52	3.79	6.23
Diameter	11.00	8.00	13.00	17.00	8.00	17.00

Note: General interest contains only the general interest journals JF, JFE, and RFS. *Field* contains the field journals JFI, JMCB, and JBF. The variables "Avg. path length" and "Diameter" were calculated using the giant component only.

Table 3: Spearman correlation for different characteristics and centralities.

Panel A: Early sample (1998-2000).

Author properties								
Papers	1.00							
Betweenness	0.14	1.00						
Eigenvector	0.20	0.69	1.00					
Degree	0.92	0.16	0.22	1.00				
Commenter properties								
Thanks	0.23	0.07	0.07	0.22	1.00			
Betweenness	0.59	0.11	0.14	0.54	0.69	1.00		
Eigenvector	0.52	0.10	0.14	0.48	0.85	0.83	1.00	
Degree	0.63	0.10	0.14	0.59	0.82	0.86	0.94	1.00

Panel B: Late sample (2009-2011).

Author properties								
Papers	1.00							
Betweenness	0.34	1.00						
Eigenvector	0.41	0.70	1.00					
Degree	0.94	0.35	0.44	1.00				
Commenter properties								
Thanks	0.03	0.20	0.18	0.03	1.00			
Betweenness	0.54	0.27	0.32	0.50	0.55	1.00		
Eigenvector	0.40	0.27	0.36	0.38	0.69	0.70	1.00	
Degree	0.63	0.28	0.36	0.61	0.61	0.90	0.80	1.00

Notes: Rank correlation coefficients for betweenness centrality and eigenvector centrality were computed for individuals that are in the giant component of both the network of formal collaboration and informal collaboration only. *Papers* is the count of an author's published research articles and *Thanks* is the number of acknowledgments a scholar was listed in.

Table 4: Top 25 researchers in the social network of formal collaboration in the early subsample (1998-200) according to different defintions.

	# of Papers		Betweenness		Eigenvector		Degree
1	Anthony Saunders (8)	1	Anthony Saunders (8)	1	Allen N Berger (6)	1	Allen N Berger (6)
2	Allen N Berger (6)	2	Allen N Berger (6)	2	Anthony Saunders (8)	2	Anthony Saunders (8)
2	Arnoud Wa Boot (6)	3	Kose John (3)	3	Gregory F Udell (2)	3	Avanidhar Subrahmanyam (5)
4	Avanidhar Subrahmanyam (5)	4	Rangarajan K Sundaram (2)	4	J David Cummins (2)	3	Michael J Barclay (3)
4	Eugene F Fama (5)	5	David L Yermack (3)	4	Mary A Weiss (2)	3	Michael S Weisbach (5)
4	Maureen O'Hara (5)	6	Anil Shivdasani (2)	6	Joseph M Scalise (1)	3	Rene M Stulz (3)
4	Michael S Weisbach (5)	7	Jun-Koo Kang (2)	7	Diana Hancock (3)	7	Jeffrey L Coles (3)
4	Paul A Gompers (5)	8	Rene M Stulz (3)	8	Hongmin Zi (1)	7	Jeffry M Netter (2)
4	Paul H Schultz (5)	9	Mark J Flannery (3)	9	Berry K Wilson (3)	7	Larry Hp Lang (3)
10	Andrei Shleifer (4)	10	Joel F Houston (3)	10	Daniel M Covitz (1)	7	Roni Michaely (4)
10	Andrew W Lo (4)	11	Berry K Wilson (3)	11	Seth D Bonime (1)	7	Wayne E Ferson (3)
10	Anjan V Thakor (4)	11	Diana Hancock (3)	12	Mark J Flannery (3)	7	William L Megginson (3)
10	Bruce D Smith (4)	11	Michael D Ryngaert (3)	13	Kose John (3)	13	Andrew D Clare (3)
10	Charles M Kahn (4)	11	Tim Opler (2)	14	Philip E Strahan (2)	13	Andrew W Lo (4)
10	Edward J Kane (4)	15	Gerard Caprio (1)	15	Sally M Davies (1)	13	Diana Hancock (3)
10	Eugene Kandel (4)	16	Edward J Kane (4)	16	Rebecca S Demsetz (1)	13	Eugene Kandel (4)
10	Franklin Allen (4)	16	Eli Ofek (2)	17	Lemma W Senbet (2)	13	Hamid Mehran (3)
10	Harrison Hong (4)	16	Manju Puri (3)	18	Gerard Caprio (1)	13	Kent L Womack (3)
10	Ivo Welch (4)	16	Philip E Strahan (2)	19	Manju Puri (3)	13	Maureen O'Hara (5)
10	Jeremy C Stein (4)	20	David B Humphrey (1)	20	Amar Gande (1)	13	Philip H Dybvig (3)
10	John R Graham (4)	21	J David Cummins (2)	22	Jianping Mei (1)	13	Randall Morck (3)
10	Joshua Lerner (4)	21	Mary A Weiss (2)	21	Lazarus A Angbazo (1)	13	Reena Aggarwal (4)
10	Kenneth R French (4)	23	Joseph M Scalise (1)	23	Sharon Tennyson (1)	13	Tim Opler (2)
10	Loretta J Mester (4)	24	Hongmin Zi (1)	24	James A Wilcox (2)	24	Ananth Madhavan (3)
10	Lubos Pastor (4)	24	Sharon Tennyson (1)	25	David B Humphrey (1)	24	Andrei Shleifer (4)

Notes: Table lists top researchers in the network in terms of number of authored papers in our dataset, betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of papers written in our dataset. Affiliation below name is the main affiliation as indicated on the last paper published during this time.

Table 5: Top 25 researchers in the social network of formal collaboration in the late subsample (2009-2011) according to different defintions.

	# of Papers		Betweenness		Eigenvector		Degree
1	Rene M Stulz (11)	1	Kose John (4)	1	Chen Lin (8)	1	Rene M Stulz (11)
2	Thomas J Chemmanur (9)	2	Itay Goldstein (4)	2	Yue Ma (5)	2	Chen Lin (8)
3	Alex Edmans (8)	3	Lucian A Bebchuk (5)	3	Joel F Houston (2)	3	Massimo Massa (8)
3	Allen N Berger (8)	4	Kj Martijn Cremers (4)	4	Yuhai Xuan (3)	3	Shane A Johnson (4)
3	Chen Lin (8)	5	Alon Brav (3)	5	Ping Lin (2)	3	Thomas J Chemmanur (9)
3	Massimo Massa (8)	6	Vinay B Nair (3)	6	Hong Zou (2)	3	Viral V Acharya (8)
3	Richard Roll (8)	7	John R Graham (4)	7	Murillo Campello (5)	7	Allen N Berger (8)
3	Robin Greenwood (8)	8	Viral V Acharya (8)	8	Paul H Malatesta (2)	7	Geert Bekaert (6)
3	Viral V Acharya (8)	9	Iftekhar Hasan (7)	9	Frank M Song (1)	9	Anthony Saunders (4)
10	Iftekhar Hasan (7)	10	Miguel A Ferreira (5)	10	James R Barth (1)	9	David A Hirshleifer (6)
10	Philip E Strahan (7)	11	Michael W Brandt (4)	11	Micah S Officer (3)	9	Iftekhar Hasan (7)
12	Amir Sufi (6)	12	Pedro Santa-Clara (2)	12	Michael Firth (2)	12	Chunchi Wu (6)
12	Avanidhar Subrahmanyam (6)	13	Campbell R Harvey (3)	14	Ping Liu (1)	12	Dimitry Livdan (6)
12	Chunchi Wu (6)	14	Allen N Berger (8)	13	Sonia Ml Wong (1)	12	Gerald J Lobo (5)
12	David A Hirshleifer (6)	15	Anthony Saunders (4)	15	John R Graham (4)	12	Henk Berkman (4)
12	Dimitry Livdan (6)	16	Bruce I Carlin (4)	16	Campbell R Harvey (3)	12	Kose John (4)
12	Geert Bekaert (6)	17	Augustin Landier (3)	17	Heitor W Almeida (3)	12	Murillo Campello (5)
12	Rudiger Fahlenbrach (6)	18	Simon Gervais (2)	18	Erasmo Giambona (2)	12	Steven Ongena (6)
12	Steven Ongena (6)	19	S Viswanathan (4)	19	Dirk Hackbarth (2)	12	Yan Leung Cheung (3)
12	Victoria Ivashina (6)	20	Terrance Odean (3)	20	Antonio F Galvao (1)	20	Alok Kumar (5)
21	Adair Morse (5)	21	Erasmo Giambona (2)	21	Kathryn L Dewenter (1)	20	Haitao Li (4)
21	Alok Kumar (5)	22	Victoria Ivashina (6)	22	Xi Han (1)	20	Ilya A Strebulaev (5)
21	Amiyatosh K Purnanandam (5)	23	Murillo Campello (5)	23	Oguzhan Ozbas (5)	20	John R Graham (4)
21	Berk A Sensoy (5)	24	Micah S Officer (3)	24	Berk A Sensoy (5)	20	Jorg Rocholl (5)
21	Christopher A Hennessy (5)	25	Rene M Stulz (11)	25	Geert Bekaert (6)	20	Karl V Lins (3)

Notes: Table lists top researchers in the network in terms of number of authored papers in our dataset, betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of papers written in our dataset. Affiliation below name is the main affiliation as indicated on the last paper published during this time.

Table 6: Top 25 researchers in the social network of informal collaboration in the early subsample (1998-200) according to different defintions.

	# of Thanks		Betweenness		Eigenvector		Degree
1	Jay R Ritter (41)	1	Rene M Stulz (25)	1	Eugene F Fama (21)	1	Allen N Berger (26)
2	Sheridan Titman (38)	2	Allen N Berger (26)	2	Luigi Zingales (23)	2	Jay R Ritter (41)
3	Raghuram G Rajan (33)	3	Andrei Shleifer (25)	3	Raghuram G Rajan (33)	3	Sheridan Titman (38)
4	Mark J Flannery (27)	4	Raghuram G Rajan (33)	4	Jay R Ritter (41)	4	Mark J Flannery (27)
5	Allen N Berger (26)	5	William L Megginson (1)	5	Andrei Shleifer (25)	5	Luigi Zingales (23)
6	Andrei Shleifer (25)	6	Jay R Ritter (41)	6	Robert W Vishny (16)	6	Raghuram G Rajan (33)
6	Rene M Stulz (25)	7	Jeffry M Netter (5)	7	Kenneth R French (18)	7	Avanidhar Subrahmanyam (15)
6	Wayne E Ferson (25)	8	Gary B Gorton (15)	8	Alon Brav (9)	7	Rene M Stulz (25)
9	Yakov Amihud (24)	9	Luigi Zingales (23)	9	Sheridan Titman (38)	9	Andrei Shleifer (25)
10	Luigi Zingales (23)	10	Sheridan Titman (38)	10	Paul A Gompers (9)	9	William L Megginson (1)
11	Steven N Kaplan (22)	11	Anil K Kashyap (14)	11	Owen A Lamont (6)	11	S Viswanathan (10)
12	Eugene F Fama (21)	12	Michael J Brennan (18)	12	John R Graham (7)	12	John R Graham (7)
12	Franklin Allen (21)	13	Wayne E Ferson (25)	13	Avanidhar Subrahmanyam (15)	13	Michael S Weisbach (10)
14	Jeremy C Stein (20)	14	Anthony Saunders (6)	14	Joshua Lerner (9)	14	Ivo Welch (8)
14	Mitchell A Petersen (20)	15	Avanidhar Subrahmanyam (15)	15	Jeremy C Stein (20)	15	Eugene F Fama (21)
16	David J Denis (19)	16	Tim Opler (14)	16	Zsuzsanna Fluck (3)	15	Wayne E Ferson (25)
17	Kenneth R French (18)	17	Mark J Flannery (27)	17	Steven N Kaplan (22)	17	Franklin Allen (21)
17	Michael J Brennan (18)	18	S Viswanathan (10)	18	Rafael La Porta (2)	18	Roni Michaely (8)
19	Ananth Madhavan (17)	19	Ananth Madhavan (17)	19	Florencio Lopez-De-Silanes (1)	19	Ananth Madhavan (17)
19	David A Hirshleifer (17)	20	Robert W Vishny (16)	20	Rene M Stulz (25)	20	Gregory F Udell (15)
19	Edward J Kane (17)	21	R Glenn Hubbard (6)	21	Ivo Welch (8)	21	Henri Servaes (11)
22	David T Brown (16)	22	Manju Puri (7)	22	Mark J Flannery (27)	21	Jeffry M Netter (5)
22	Robert W Vishny (16)	23	Randall S Kroszner (5)	23	Brad M Barber (10)	23	Gary B Gorton (15)
24	Avanidhar Subrahmanyam (15)	24	Maureen O'Hara (13)	24	Allen N Berger (26)	23	Michel A Habib (6)
24	Charles W Calomiris (15)	25	Olivier J Blanchard (6)	25	David A Hirshleifer (17)	25	Anthony Saunders (6)

Notes: Table lists top researchers in the network in terms of number of thanks, betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of thanks in our dataset. Affiliation below name is the main affiliation as indicated on the last paper published during this time.

Table 7: Top 25 researchers in the social network of informal collaboration in the late subsample (2009-2011) according to different defintions.

	# of Thanks		Betweenness		Eigenvector		Degree
1	Jeremy C Stein (67)	1	Rene M Stulz (44)	1	Alex Edmans (25)	1	Viral V Acharya (29)
2	Michael R Roberts (45)	2	G Andrew Karolyi (28)	2	Amir Sufi (21)	2	Rene M Stulz (44)
3	Rene M Stulz (44)	3	Viral V Acharya (29)	3	Michael R Roberts (45)	3	Alex Edmans (25)
4	Mitchell A Petersen (43)	4	Hans Degryse (17)	4	Jeremy C Stein (67)	4	Avanidhar Subrahmanyam (21)
5	Andrei Shleifer (42)	5	Yakov Amihud (39)	5	Amiyatosh K Purnanandam (12)	5	Yakov Amihud (39)
6	Douglas W Diamond (41)	6	Geert Bekaert (12)	6	Joshua D Rauh (21)	6	Massimo Massa (12)
6	John Y Campbell (41)	7	Allen N Berger (13)	7	Xavier Gabaix (27)	7	Jeremy C Stein (67)
8	J Darrell Duffie (40)	8	Stijn G Van Nieuwerburgh (9)	8	Rene M Stulz (44)	8	G Andrew Karolyi (28)
9	Yakov Amihud (39)	9	John Y Campbell (41)	9	Viral V Acharya (29)	9	Raman Uppal (25)
10	Sheridan Titman (37)	10	Avanidhar Subrahmanyam (21)	10	Bruce I Carlin (6)	10	Sheridan Titman (37)
11	Franklin Allen (36)	11	Campbell R Harvey (29)	11	Sudheer Chava (6)	11	Richard Roll (8)
12	Jay R Ritter (33)	12	Michael W Brandt (22)	12	Robin Greenwood (12)	12	Allen N Berger (13)
12	Lubos Pastor (33)	13	Iftekhar Hasan (8)	13	Efraim Benmelech (7)	13	Ravi Jagannathan (30)
14	Antoinette Schoar (31)	14	Itay Goldstein (18)	14	Steven N Kaplan (30)	14	Michael R Roberts (45)
14	Michael S Weisbach (31)	15	Anthony Saunders (16)	15	Lucian A Taylor (9)	14	Steven Ongena (22)
16	John H Cochrane (30)	16	Jay R Ritter (33)	16	Itay Goldstein (18)	16	Tarun Chordia (11)
16	Malcolm P Baker (30)	17	Ravi Jagannathan (30)	17	Douglas W Diamond (41)	17	J Darrell Duffie (40)
16	Philip E Strahan (30)	18	Victoria Ivashina (14)	18	Berk A Sensoy (9)	18	Andrei Shleifer (42)
16	Ravi Jagannathan (30)	19	Franklin Allen (36)	19	Mitchell A Petersen (43)	18	Xavier Gabaix (27)
16	Steven N Kaplan (30)	20	Mara Faccio (18)	20	Andrei Shleifer (42)	20	Ronald W Masulis (23)
21	Bernard Dumas (29)	21	Raman Uppal (25)	21	Gustavo Manso (8)	21	John M Griffin (16)
21	Campbell R Harvey (29)	22	Massimo Massa (12)	22	Victoria Ivashina (14)	21	S Viswanathan (20)
21	Patrick Bolton (29)	23	Haitao Li (3)	23	Franklin Allen (36)	23	Hans Degryse (17)
21	Viral V Acharya (29)	24	Kose John (21)	24	John R Graham (21)	24	Thomas J Chemmanur (9)
25	G Andrew Karolyi (28)	25	John M Griffin (16)	25	Malcolm P Baker (30)	25	Andrew Metrick (23)

Notes: Table lists top researchers in the network in terms of number of thanks, betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of thanks in our dataset. Affiliation below name is the main affiliation as indicated on the last paper published during this time.

Table 8: Summary statistics for 100 most often thanked, most betweenness central and most eigenvector central academics, early subset (1998-2000).

Panel A: Number of thanks.

Statistic	N	Mean	St. Dev.	Min	Max
Rank of PhD aff.	81	33.086	58.504	1	295
Rank cur. aff.	79	118.848	214.599	1	856
Female	85	0.012	0.108	0	1
Editorship years	85	15.800	34.320	0	244
Membership	85	0.224	0.419	0	1
Seniority	80	28.988	7.154	16	54
# of Thanks	110	13.500	6.026	9	41

Panel B: Betweenness centrality.

Statistic	N	Mean	St. Dev.	Min	Max
Rank of PhD aff.	79	40.038	58.144	1	295
Rank cur. aff.	73	156.726	236.237	1	936
Female	85	0.024	0.152	0	1
Editorship years	85	15.706	34.233	0	244
Membership	85	0.235	0.427	0	1
Seniority	78	27.692	6.690	16	54
# of Thanks	100	9.530	8.486	0	41

Panel C: Eigenvector centrality.

Statistic	N	Mean	St. Dev.	Min	Max
Rank of PhD aff.	93	33.323	81.440	1	645
Rank cur. aff.	87	103.241	193.301	1	856
Female	94	0.032	0.177	0	1
Editorship years	94	12.543	31.060	0	244
Membership	94	0.234	0.426	0	1
Seniority	85	26.012	7.087	15	51
# of Thanks	100	10.190	8.267	0	41

Notes: Summary statistics for 100 most often acknowledged and most central researchers in the social network of informal collaboration from 1998 to 2000. *Variables: Rank of PhD aff.* is the Tilburg Economics Department rank as of 2013 of the graduate school; *Rank of cur. aff.* is the Tilburg Economics Department rank as of 2013 of affiliation in 2012; *Female* is a binary variable indicating female sex; *Editorship years* is the sum of years a researcher has been serving as managing or associate editor per journal; *Membership* is a binary variable indicating membership/affiliation in National Bureau of Economic Research and/or Centre for Economic Policy Research during the 2000s; *Seniority* is the duration in years between 2010 and the year in which the PhD was awarded; *# of Thanks* is the number of papers in our dataset that acknowledge the researcher during 1998-2000. Column N indicates the number of persons in the set for which the corresponding observations are available.

Table 9: Results of ordinal regression for 100 most central researchers in the early social network of informal collaboration.

	# of Thanks	Betweenness centr.	Eigenvector centr.
Rank of PhD aff.	-0.00004	0.003	-0.002
	(0.003)	(0.003)	(0.002)
Rank cur. aff.	0.0004	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Female	-0.374	-0.633	0.096
	(1.559)	(1.113)	(1.096)
Editorship years	0.008	-0.012^{*}	0.0001
	(0.006)	(0.007)	(0.006)
Membership	0.138	-0.605	-0.171
	(0.509)	(0.515)	(0.438)
Seniority	0.209	-0.088	0.669^{***}
	(0.164)	(0.159)	(0.179)
Seniority^2	-0.003	0.002	-0.010^{***}
	(0.003)	(0.002)	(0.003)
# of Thanks		-0.136^{***}	-0.181^{***}
		(0.026)	(0.030)
N	110	100	100
Log Likelihood	-265.981	-434.553	-439.414

Notes: ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. Reported coefficients are proportional odds ratios. Dependent variable is the rank according to the number of thanks, betweenness centrality or eigenvector centrality. Missing values were mean-imputed. *Variables: Betweenness centrality* of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). *Eigenvector centrality* of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. *Rank of PhD aff.* is the Tilburg Economics Department rank as of 2013 of the graduate school; *Rank of cur. aff.* is the Tilburg Economics Department rank as of 2013 of affiliation in 2012; *Female* is a binary variable indicating female sex; *Editorship years* is the sum of years a researcher has been serving as managing or associate editor per journal; *Membership* is a binary variable indicating membership/affiliation in National Bureau of Economic Research and/or Centre for Economic Policy Research during the 2000s; *Seniority* is the duration in years between 2010 and the year in which the PhD was awarded; *# of Thanks* is the number of papers in our dataset that acknowledge the researcher during 1998-2000.

Table 10: Summary statistics for 100 most often thanked, most betweenness central and most eigenvector central academics, late subset (2009-2011).

Panel A: Number of thanks.

Statistic	N	Mean	St. Dev.	Min	Max
Rank of PhD aff.	86	48.709	138.625	1	911
Rank cur. aff.	80	110.200	209.594	1	781
Female	88	0.068	0.254	0	1
Editorship years	88	12.193	31.898	0	244
Membership	88	0.443	0.500	0	1
Seniority	84	23.440	9.341	7	51
# of Thanks	104	24.615	8.056	17	67

Panel B: Betweenness centrality.

Statistic	N	Mean	St. Dev.	Min	Max
Rank of PhD aff.	93	78.151	144.065	1	911
Rank cur. aff.	82	149.341	207.487	1	781
Female	95	0.053	0.224	0	1
Editorship years	95	12.958	35.255	0	244
Membership	95	0.221	0.417	0	1
Seniority	86	21.849	9.414	7	46
# of Thanks	100	15.760	11.835	0	67

Panel C: Eigenvector centrality.

Statistic	N	Mean	St. Dev.	Min	Max
Rank of PhD aff.	97	29.010	90.882	1	659
Rank cur. aff.	96	125.635	232.466	1	781
Female	99	0.040	0.198	0	1
Editorship years	99	9.909	32.704	0	244
Membership	99	0.374	0.486	0	1
Seniority	98	17.653	9.627	5	50
# of Thanks	100	19.110	11.770	2	67

Notes: Summary statistics for 100 most often acknowledged and most central researchers in the social network of informal collaboration from 2009 to 2011. *Variables: Rank of PhD aff.* is the Tilburg Economics Department rank as of 2013 of the graduate school; *Rank of cur. aff.* is the Tilburg Economics Department rank as of 2013 of affiliation in 2012; *Female* is a binary variable indicating female sex; *Editorship years* is the sum of years a researcher has been serving as managing or associate editor per journal; *Membership* is a binary variable indicating membership/affiliation in National Bureau of Economic Research and/or Centre for Economic Policy Research during the 2000s; *Seniority* is the duration in years between 2010 and the year in which the PhD was awarded; *# of Thanks* is the number of papers in our dataset that acknowledge the researcher during 2009-2011. Column N indicates the number of persons in the set for which the corresponding observations are available.

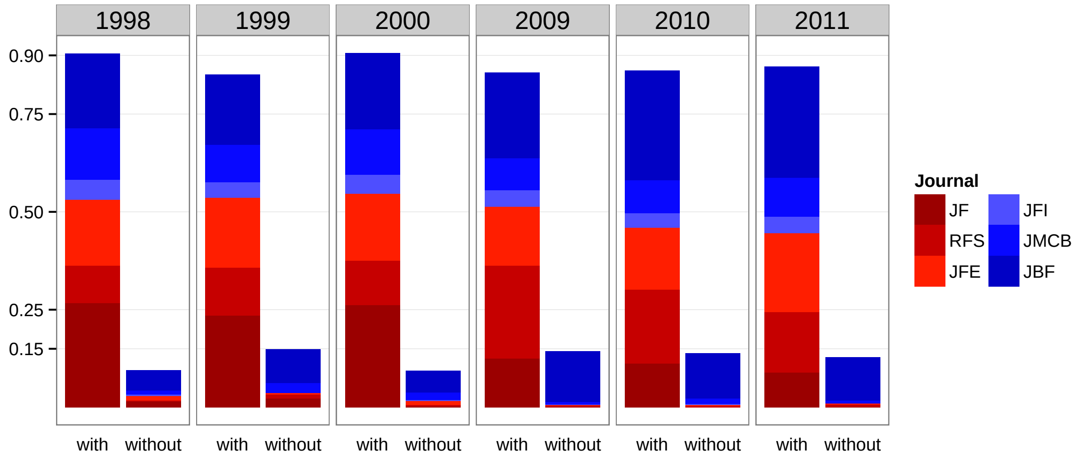
Table 11: Results of ordinal regression for 100 most central researchers in the late social network of informal collaboration.

	# of Thanks	Betweenness centr.	Eigenvector centr.
Rank of PhD aff.	-0.005^{***}	-0.002^{*}	-0.003^{*}
	(0.002)	(0.001)	(0.002)
Rank cur. aff.	0.0003	0.001	-0.0002
	(0.001)	(0.001)	(0.001)
Female	-1.241	1.420^{*}	1.546^{*}
	(0.955)	(0.809)	(0.873)
Editorship years	0.016^{***}	-0.009	-0.007
	(0.006)	(0.006)	(0.006)
Membership	0.636	0.163	0.006
	(0.407)	(0.513)	(0.378)
Seniority	0.215^{**}	-0.063	0.392^{***}
	(0.091)	(0.101)	(0.093)
Seniority^2	-0.003^{**}	0.001	-0.006^{***}
	(0.002)	(0.002)	(0.002)
# of Thanks		-0.059^{***}	-0.137^{***}
		(0.020)	(0.024)
N	104	100	100
Log Likelihood	-289.499	-450.048	-437.619

Notes: ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. Reported coefficients are proportional odds ratios. Dependent variable is the rank according to the number of thanks, betweenness centrality or eigenvector centrality. Missing values were mean-imputed. *Variables: Betweenness centrality* of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). *Eigenvector centrality* of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). *Rank of PhD aff.* is the Tilburg Economics Department rank as of 2013 of the graduate school; *Rank of cur. aff.* is the Tilburg Economics Department rank as of 2013 of affiliation in 2012; *Female* is a binary variable indicating female sex; *Editorship years* is the sum of years a researcher has been serving as managing or associate editor per journal; *Membership* is a binary variable indicating membership/affiliation in National Bureau of Economic Research and/or Centre for Economic Policy Research during the 2000s; *Seniority* is the duration in years between 2010 and the year in which the PhD was awarded; *# of Thanks* is the number of papers in our dataset that acknowledge the researcher during 2009-2011.

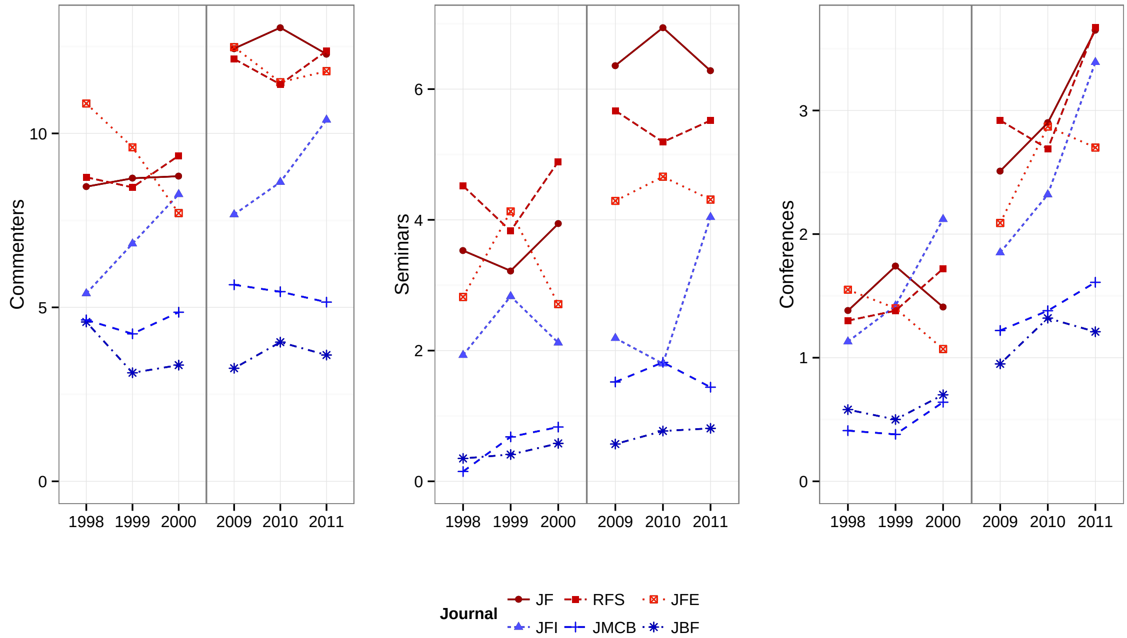
A.2. Figures

Figure 1: Share of articles with and without acknowledgements per journal and year.



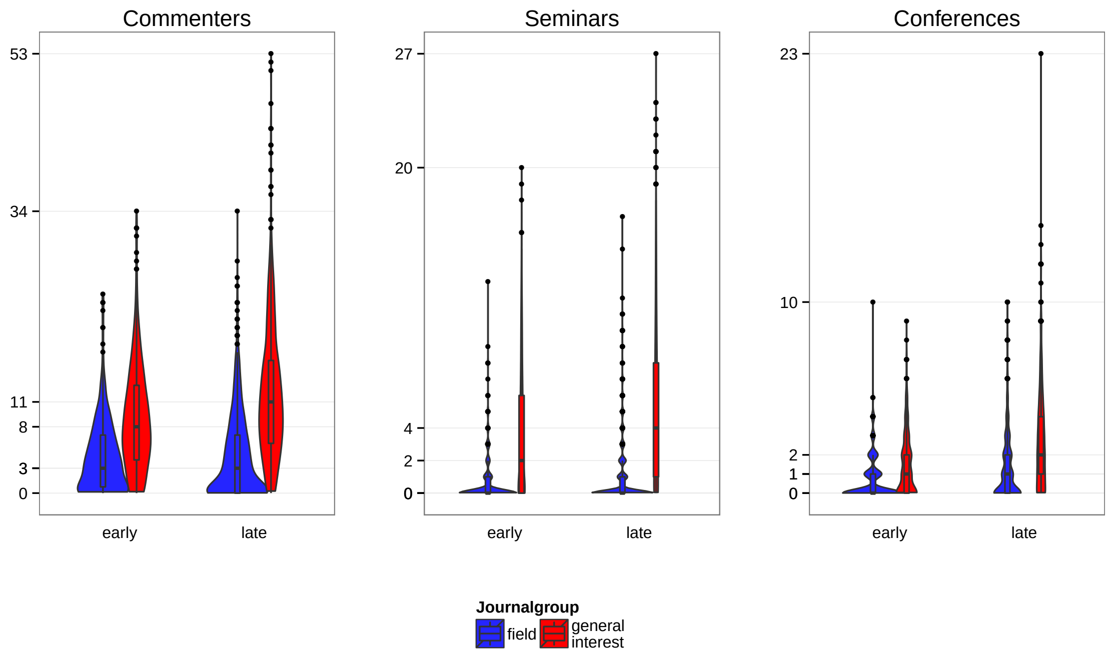
Notes: Graph shows share of articles with (left bar) and without acknowledgments (right bar) for each year. Colors correspond to journals, where reddish colors refer to general interest journals.

Figure 2: Mean number of commenters, seminars and conferences over time per journal and year.



Notes: Graph shows mean number of acknowledged commenters (left plot), seminars (center plot) and conferences (right plot) per journal over time. Colors correspond to journals, where reddish colors refer to general interest journals.

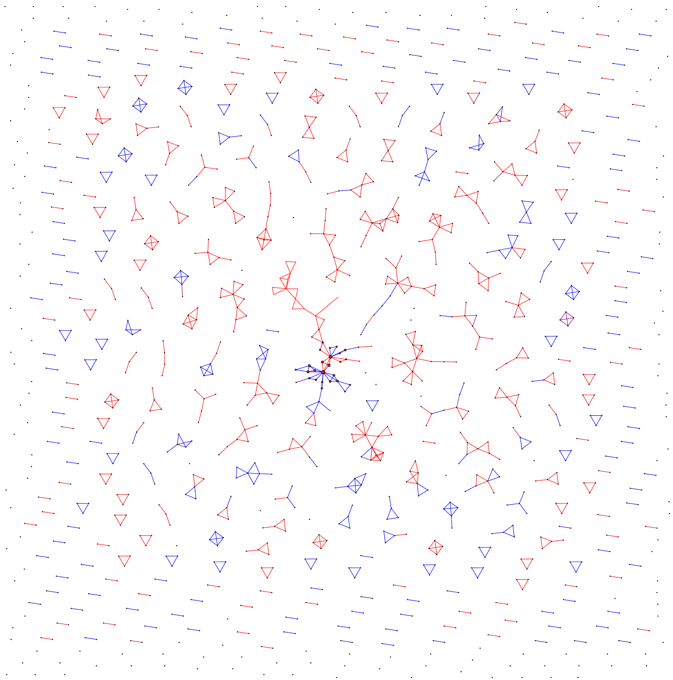
Figure 3: Distribution of commenters, seminars and conferences acknowledged on all papers per timepoint and journalgroup.



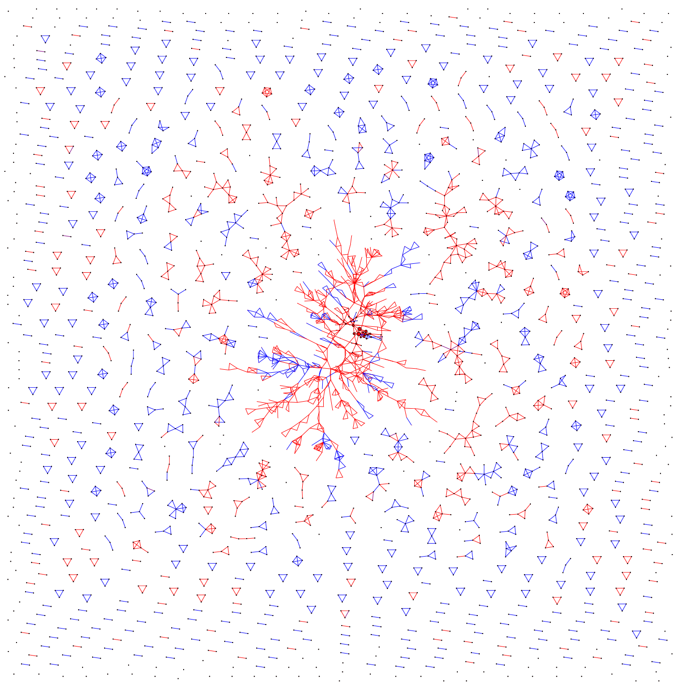
Notes: Graph shows distribution of the number of acknowledged commenters (left plot), seminars (center plot) and conferences (right plot) per journalgroup in comparison for the early and the late timepoint. Distribution is shown by a combined box-violinplot: The thicker the violin, the higher the density at this point. The rectangle inside the violin symbolizes the inner quartile, being the range between the 25%-quantile and the 75%-quantile. Points at the upper tail visualize outliers, defined as being more extreme than 1.5 times the inner-quartile range.

Figure 4: Social network of formal collaboration (co-Author network) by timepoint

(a) Early (1998-2000)



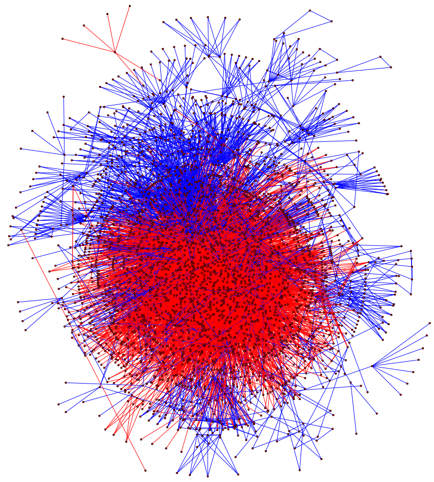
(b) Late (2009-2011)



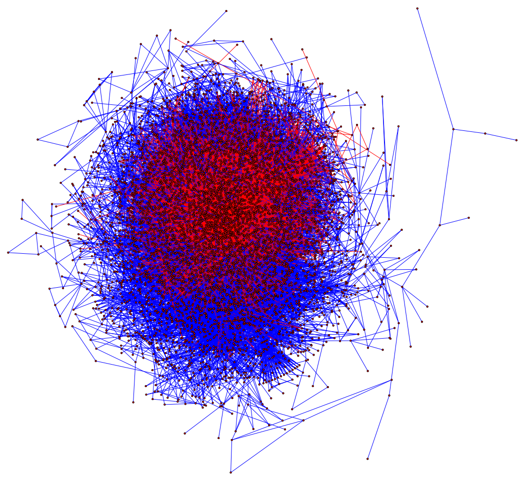
Notes: A link is drawn between every co-author of a published research article. Red links indicate that the research article was published in a general interest journal, while blue indicates a field journal publication. If a link occurs in both a general interest journal and a field journal, which is a rare event, it is colored in purple. Graph representation using and adapted of Fruchterman-Reingold algorithm.

Figure 5: Social network of informal collaboration (commenter network) by timepoint

(a) Early (1998-2000)



(b) Late (2009-2011)



Notes: A link is drawn between an acknowledged commenter and every author of a published research article. Red links indicate that the research article was published in a general interest journal, while blue indicates a field journal publication. If a link occurs in both a general interest journal and a field journal, which is a rare event, it is colored in purple. Only the giant component is shown. Graph representation using and adapted of Fruchterman-Reingold algorithm.

B. Online Appendix

B.1. Network nomenclature

We introduce some graph theory in order to examine the network structure. Formally, let P_t be the number of articles in $t \in \text{early}, \text{late}$, where early refers to papers published between 1998 and 2000 and late refers to publications between 2009 and 2011. To each paper $p \in P_t$, there is a set of authors κ_p and a set of commenters ι_p. Every author $k \in \kappa_p$ is part of the set of nodes of the social network of formal collaboration S^F (or co-author network) and also part of the set of nodes of the social network of informal collaboration S^I. Every commenter $i \in \iota_p$ is part a of the social network of informal collaboration S^I. Of course, i can equal k, namely when an author comments on the work of others.

A link between two academics $k, l \in S^F$ in the social network of formal collaboration is denoted s_{kl}^F and takes the values $\{0, 1, \ldots \bar{l}^c\}$ where $\bar{l}^c$ is the maximum number of papers academics have co-authored. The set of all s_{kl}^F forms the symmetric adjacency matrix of the co-author network S^F. Similarly, a link between two academics $i, k \in S^I$ in the network of informal collaboration is denoted s_{ik}^I and takes values $\{w_{ik} \in \mathbb{R}_{0,+}$. w_{ik} reflects a weighting scheme to account for possible misspecification of author-commenter-ties. w_{ik} increases by $1/\mid \kappa_p \mid$ if author i acknowledges commenter k on paper p. If the commenter has been acknowledged once on a paper written by two authors, the weight of each of the two links would be 1/2. If one of the author acknowledges this commenter on another solo-paper, the link increases to 3/2, reflecting a deeper relationship. k may, however, also be a co-author of i, in which case w_{ik} increases by 1. The adjacency matrix of the acknowledgement network is symmetric as acknowledgements are undirected. Hence, if k is author and i commenter, the same weighting scheme applies.

The set of co-authors of academic k in the co-author network S^F is denoted $\mathcal{N}_i(S^F) = \{j | g_{kj}^c \geq 0\}$. The number of co-authors of academic K, also denoted academic K's degree, is given by $|\mathcal{N}_i(S^F)|$. Same logic applies to the social network of informal collaboration S^I.

Using the density of each node we can characterize network density. Density is defined as the share of realized paths $\sum_{i,j}^{S} s_{ij}$ on the number of potential paths $\frac{n(n-1)}{2}$ given the network size n:

$$\text{density} = \sum_{i,j}^{S} s_{ij} \frac{2}{n(n-1)} \tag{6}$$

Density measures the network's efficiency in information transmission. The higher the number, the more potential connections are realized and thus the faster the transmission.

In real world networks it is common that nodes are not connected, not even with intermediate steps. Formally, two nodes belong to the same network component l if there exists a path between them. There can be as many components as there are nodes, is the case if all nodes are isolated, but at least one component. A network component of a directed graph is said to be weakly connected if there is a path between any two nodes in the component when the directionality is ignored. The size of a component is the number of nodes (i.e. the number of academics) it contains. If a node i belongs to a small network component, all other nodes are fairly close. In contrast, a node in a large network might have a potentially much smaller centrality because many other nodes are far away.

Within the same component we can compute network centralities because most centrality definitions rely on paths. Centralities in essence give a ranking of nodes to make their position comparable; the actual number is often meaningless. We present four centrality measures: count of (direct) neighbors or degree, count of indirect neighbors, betweenness centrality and eigenvector centrality. The count of direct and indirect neighbors are trivial by definition and answer the question: How many academics can this academic reach directly (indirectly)? It is a proxy for communicative activity.

Betweenness centrality is a more complex measure and was first published by

Freeman (1979). Denote the shortest path between j and k in network g as $\sigma_{jk}(l)$ and the number of shortest paths between j and k that contain node i as $\sigma_{jk}(i|l)$. Betweenness centrality $C_B(i;l)$ of node i in network l is then given as:

$$C_B(i;l) = \sum_{j,k \in N} \frac{\sigma_{jk}(i|l)}{\sigma_{jk}(l)} \tag{7}$$

Betweenness centrality is thus the probability that node i is on a shortest path between any two nodes in component l. Recall, that each link resembles a social relationship, i.e. the exchange of information, either formally in the co-author network or informally in the acknowledgement network. A high betweenness centrality indicates that the academic is relevant for most communication processes inside the network. In this case, the academic can excel power by simply deterring or preventing information flows. It also suggests that communication flows will dry out if these nodes were removed from the network.

The eigenvector centrality is our fourth centrality measure. It weights the adjacent nodes with their respective eigenvector centrality (Bonacich, 1986). Typically, high eigenvector central nodes are clustered together meaning that eigenvector centrality points to the best connected nodes in a network. For academic i it is defined as:

$$C_E(i;l) = \frac{1}{\lambda} \sum_{j}^{\mathcal{N}_i} g_{i,j} \cdot eigenvector(j), \tag{8}$$

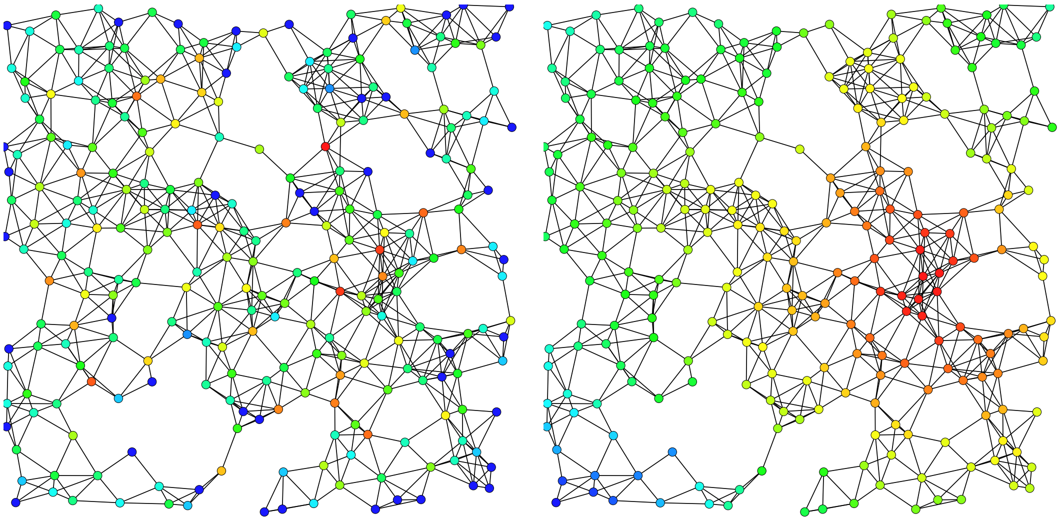
where $\lambda \neq 0$ is a constant. The term $\frac{1}{\lambda}$ normalizes the measure. Written in matrix notation, the formula yields

$$\lambda \cdot \mathbf{eigenvector} = \mathbf{eigenvector} \cdot \mathbf{N} \tag{9}$$

which is precisely the definition of eigenvalues (in this case the eigenvalue is λ). Put differently, the vector containing the eigenvector centralities for all the nodes is the eigenvector associated with matrix $\mathbf{A}$'s eigenvalue λ. By virtue of the Perron-Frobenius Theorem, the equality of λ and $\mathbf{N}$'s largest eigenvalue λ_{max} ensures a unique

Figure 6: Illustration of centrality measures

(a) Betweenness centrality (b) Eigenvector centrality



Note: Illustration of two centrality measures for the same hypothetical network of 256 nodes. Red indicates nodes with high values and blue indicates nodes with low values.

and positive solution. Eigenvector centrality is high when an academic knows many academics or few academic in central places, or both.

Though all the centrality measures are related, they focus on different aspects. Figure 6 compares all four centrality measures that we use on the same (example) network. To broker between groups requires a high betweenness centrality (6a). Very eigenvector central nodes (6b) are likely to be the center of the best-connected clique in a network. The centrality decreases evenly in concentric rings from the most eigenvector central node.

B.2. Top 100 lists

Table 12: Most central researchers in the social network of formal collaboration in the early subsample (1998-200) - rank 26 through 100

	Betweenness		Eigenvector		Degree
1	Anthony Saunders (8)	1	Allen N Berger (6)	24	Arnoud Wa Boot (6)
2	Allen N Berger (6)	2	Anthony Saunders (8)	24	B Espen Eckbo (3)
3	Kose John (3)	3	Gregory F Udell (2)	24	Bruce D Smith (4)
4	Rangarajan K Sundaram (2)	4	J David Cummins (2)	24	Charles Cao (2)
5	David L Yermack (3)	4	Mary A Weiss (2)	24	Charles M Kahn (4)
6	Anil Shivdasani (2)	6	Joseph M Scalise (1)	24	Daniel Levy (2)
7	Jun-Koo Kang (2)	7	Diana Hancock (3)	24	David L Yermack (3)
8	Rene M Stulz (3)	8	Hongmin Zi (1)	24	Dong-Hyun Ahn (2)
9	Mark J Flannery (3)	9	Berry K Wilson (3)	24	Eric C Chang (3)
10	Joel F Houston (3)	10	Daniel M Covitz (1)	24	Franklin Allen (4)
11	Berry K Wilson (3)	11	Seth D Bonime (1)	24	Henri Servaes (3)
11	Diana Hancock (3)	12	Mark J Flannery (3)	24	Ike Mathur (2)
11	Michael D Ryngaert (3)	13	Kose John (3)	24	Ivo Welch (4)
11	Tim Opler (2)	14	Philip E Strahan (2)	24	J David Cummins (2)
15	Gerard Caprio (1)	15	Sally M Davies (1)	24	J Harold Mulherin (2)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the

Table 12: *(continued)*

	Betweenness		Eigenvector		Degree
16	Edward J Kane (4)	16	Rebecca S Demsetz (1)	24	Jacob Boudoukh (2)
16	Eli Ofek (2)	17	Lemma W Senbet (2)	24	Jeff Fleming (2)
16	Manju Puri (3)	18	Gerard Caprio (1)	24	Jeffrey H Harris (2)
16	Philip E Strahan (2)	19	Manju Puri (3)	24	Jeremy C Stein (4)
20	David B Humphrey (1)	20	Amar Gande (1)	24	Joel F Houston (3)
21	J David Cummins (2)	22	Jianping Mei (1)	24	Josef Lakonishok (2)
21	Mary A Weiss (2)	21	Lazarus A Angbazo (1)	24	Jun-Koo Kang (2)
23	Joseph M Scalise (1)	23	Sharon Tennyson (1)	24	Katrina Ellis (2)
24	Hongmin Zi (1)	24	James A Wilcox (2)	24	Kee H Chung (2)
24	Sharon Tennyson (1)	25	David B Humphrey (1)	24	Kerry E Back (2)
26	Amar Gande (1)	26	Edward J Kane (4)	24	Kose John (3)
26	Andy Naranjo (3)	27	Rangarajan K Sundaram (2)	24	Loretta J Mester (4)
26	Armen Hovakimian (1)	28	Joel F Houston (3)	24	Luigi Zingales (4)
26	Bong-Chan Kho (1)	29	Viral V Acharya (1)	24	Mai Iskandar-Datta (3)
26	Charles J Hadlock (1)	30	James P Weston (2)	24	Mary A Weiss (2)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 12: *(continued)*

	Betweenness		Eigenvector		Degree
26	Christopher M James (1)	31	Michael D Ryngaert (3)	24	Matthew Richardson (2)
26	Daniel M Covitz (1)	32	Thomas Hellmann (1)	24	Michael D Ryngaert (3)
26	Gregory F Udell (2)	34	Andy Naranjo (3)	24	Michael L Lemmon (2)
26	Hyuk Choe (1)	33	Mahendrarajah Nimalendran (3)	24	Neil D Pearson (3)
26	James A Wilcox (2)	35	Charles J Hadlock (1)	24	Owen A Lamont (4)
26	James P Weston (2)	36	David L Yermack (3)	24	Paul H Schultz (5)
26	Jennifer E Bethel (1)	37	Menachem Brenner (1)	24	Paul S Calem (2)
26	Jianping Mei (1)	38	Armen Hovakimian (1)	24	Pierluigi Balduzzi (3)
26	Julia Porter Liebeskind (1)	39	Christopher M James (1)	24	Raman Kumar (2)
26	Lazarus A Angbazo (1)	40	Anil Shivdasani (2)	24	Rangarajan K Sundaram (2)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of papers written in our dataset.

Table 12: *(continued)*

	Betweenness		Eigenvector		Degree
26	Lee Pinkowitz (1)	41	Eli Ofek (2)	24	Raphael W Bostic (2)
26	Lemma W Senbet (2)	42	Jun-Koo Kang (2)	24	Robert B Avery (2)
26	Mahendrarajah Nimalendran (3)	43	Takeshi Yamada (1)	24	Robert F Whitelaw (3)
26	Menachem Brenner (1)	44	Philip G Berger (1)	24	Robert L Kieschnick (2)
26	Philip G Berger (1)	45	Rene M Stulz (3)	24	Robert W Vishny (3)
26	Rebecca S Demsetz (1)	46	Yong-Cheol Kim (1)	24	S Viswanathan (4)
26	Rohan Williamson (1)	47	Tim Opler (2)	24	Stephen H Thomas (3)
26	Sally M Davies (1)	49	Lee Pinkowitz (1)	24	Sudip Datta (3)
26	Seth D Bonime (1)	48	Rohan Williamson (1)	24	Tarun Chordia (3)
26	Takeshi Yamada (1)	50	Bong-Chan Kho (1)	24	Vincent A Warther (3)
26	Thomas Hellmann (1)	51	Hyuk Choe (1)	24	Vojislav Maksimovic (4)
26	Viral V Acharya (1)	52	Jennifer E Bethel (1)	24	William G Christie (2)
26	Yong-Cheol Kim (1)	53	Julia Porter Liebeskind (1)	78	A Craig Mackinlay (2)
				78	Aigbe Akhigbe (3)
				78	Ajay Khorana (2)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 12: *(continued)*

	Betweenness		Eigenvector		Degree
				78	Alan K Reichert (1)
				78	Alasdair Breach (1)
				78	Alex Frino (1)
				78	Allan Timmermann (2)
				78	Andre Lucas (1)
				78	Anil Shivdasani (2)
				78	Anjan V Thakor (4)
				78	Anthony Neuberger (3)
				78	Antonella Foglia (2)
				78	Atulya Sarin (2)
				78	Bengt Turner (1)
				78	Bernadette A Minton (2)
				78	Berry K Wilson (3)
				78	Bhaskaran Swaminathan (3)
				78	Brad M Barber (2)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 12: *(continued)*

	Betweenness		Eigenvector		Degree
				78	Brian F Smith (2)
				78	Brian Jorgenson (1)
				78	Campbell R Harvey (3)
				78	Carl-Heinrich Kehr (1)
				78	Charles A Trzcinka (2)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of papers written in our dataset.

Table 13: Most central researchers in the social network of formal collaboration in the late subsample (2009-2011) - rank 26 through 100

	Betweenness		Eigenvector		Degree
26	David S Scharfstein (3)	26	Michelle Lowry (2)	20	Martin Brown (4)
27	Jorg Rocholl (5)	27	G William Schwert (1)	20	Miguel A Ferreira (5)
28	Henrik Cronqvist (3)	28	Michael W Brandt (4)	20	Philip E Strahan (7)
29	Geert Bekaert (6)	30	Gongmeng Chen (1)	20	Richard Stanton (5)
30	Darius P Miller (2)	29	Liping Xu (1)	20	Robin Greenwood (8)
31	Stephan Siegel (2)	31	Alok Kumar (5)	20	Sheri Tice (3)
32	Nuno Fernandes (2)	32	Alon Brav (3)	20	Stijn G Van Nieuwerburgh (4)
33	Massimo Massa (8)	33	Stephan Siegel (2)	20	Vinay B Nair (3)
34	Yu-Jane Liu (2)	34	Christian T Lundblad (2)	34	Alon Brav (3)
35	Rudiger Fahlenbrach (6)	35	Jules H Van Binsbergen (2)	34	Avanidhar Subrahmanyam (6)
36	Oguzhan Ozbas (5)	36	Jie Yang (1)	34	Eugene Kandel (3)
37	Debarshi K Nandy (3)	37	Marti G Subrahmanyam (2)	34	G Andrew Karolyi (5)
38	Kjell G Nyborg (3)	38	Daniel Wolfenzon (1)	34	Hassan Tehranian (3)
39	Chen Lin (8)	39	Sang Yong Park (1)	34	Hendrik Bessembinder (3)
40	David J Thesmar (4)	40	Ran Duchin (3)	34	Henrik Cronqvist (3)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the

Table 13: *(continued)*

	Betweenness		Eigenvector		Degree
41	Sascha Steffen (3)	41	Xiaoyan Zhang (4)	34	Itay Goldstein (4)
42	Timothy C Johnson (2)	42	Robert J Hodrick (3)	34	John M Griffin (4)
43	Alex Edmans (8)	43	Joseph Golec (1)	34	Jun-Koo Kang (3)
44	Prachi Deuskar (2)	44	Alessandro Beber (3)	34	Kai Li (3)
45	Wei Jiang (3)	45	Kenneth A Kavajecz (2)	34	Kj Martijn Cremers (4)
46	Ilya A Strebulaev (5)	46	Yuhang Xing (3)	34	Lucian A Bebchuk (5)
47	Kai Li (3)	47	Levent Guntay (1)	34	Michael W Brandt (4)
48	Yaniv Grinstein (2)	48	John G Matsusaka (1)	34	Michel Beine (3)
49	Anna Kovner (3)	49	Per Stromberg (3)	34	Peter Bossaerts (3)
50	Robin Greenwood (8)	50	Steven N Kaplan (2)	34	Philip Molyneux (4)
51	Vidhi Chhaochharia (3)	51	Andrew Ang (3)	34	Richard Roll (8)
52	Jules H Van Binsbergen (2)	52	David S Scharfstein (3)	34	Ronald W Masulis (5)
53	Thomas J Chemmanur (9)	53	Itay Goldstein (4)	34	Sheridan Titman (4)
54	Philip Bond (3)	54	Wei Jiang (3)	34	Sumit Agarwal (3)
55	Ralph Sj Koijen (3)	55	Eric Engstrom (1)	34	Takeshi Nishikawa (3)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 13: *(continued)*

	Betweenness		Eigenvector		Degree
56	Xiaoyan Zhang (4)	56	Lior Menzly (1)	34	Victoria Ivashina (6)
57	W Scott Frame (3)	57	Ola Bengtsson (1)	34	Yue Ma (5)
58	Bernadette A Minton (2)	58	Antonio Moreno (1)	58	Adair Morse (5)
59	Vikram K Nanda (4)	59	Koen Inghelbrecht (1)	58	Ajai K Singh (2)
60	David K Musto (2)	61	Lieven Baele (1)	58	Alexander W Butler (4)
61	Lu Zheng (3)	60	Seonghoon Cho (1)	58	Amit Seru (3)
62	Luc Laeven (3)	62	Michael D Bradley (1)	58	Andrew Ang (3)
63	G Andrew Karolyi (5)	63	Rossen Valkanov (2)	58	Andrew Metrick (3)
64	Eugene Kandel (3)	64	Pedro Santa-Clara (2)	58	Anna Kovner (3)
65	Adam V Reed (2)	65	G David Haushalter (2)	58	Berk A Sensoy (5)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of papers written in our dataset.

Table 13: *(continued)*

	Betweenness		Eigenvector		Degree
66	Andrew Metrick (3)	66	Warren Bailey (2)	58	Campbell R Harvey (3)
67	Paul Wachtel (2)	67	Henrik Cronqvist (3)	58	Christopher J Malloy (3)
68	Steven Ongena (6)	68	Oliver G Spalt (2)	58	Cnv Krishnan (2)
69	Hyun Song Shin (3)	69	David Ng (1)	58	Dan Li (3)
70	Paul A Gompers (2)	70	Jeremy K Page (1)	58	Darius P Miller (2)
71	Haitao Li (4)	71	Amir Barnea (1)	58	Debarshi K Nandy (3)
72	Adam B Ashcraft (2)	72	Andrew Ellul (1)	58	Doron Avramov (2)
72	Harjoat S Bhamra (3)	73	Chotibhak Jotikasthira (1)	58	Douglas D Evanoff (2)
72	Soehnke M Bartram (2)	74	George M Korniotis (1)	58	Guofu Zhou (4)
75	Joshua Lerner (3)	75	Richmond D Mathews (1)	58	Hans Degryse (3)
76	Gustavo Manso (4)	76	Haitao Li (4)	58	Hao Zhou (4)
77	Geraldo Cerqueiro (2)	77	Ralph Sj Koijen (3)	58	Heitor W Almeida (3)
78	Raman Uppal (3)	78	Amrut Nashikkar (2)	58	Hsuan-Chi Chen (4)
79	Adair Morse (5)	79	Rainer Jankowitsch (1)	58	Jeong-Bon Kim (4)
80	Craig Doidge (4)	80	Chunchi Wu (6)	58	John M Bizjak (3)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 13: *(continued)*

	Betweenness		Eigenvector		Degree
81	Alok Kumar (5)	81	Yuewu Xu (1)	58	John Y Campbell (3)
82	Yuhang Xing (3)	82	Vineer Bhansali (1)	58	Joshua Lerner (3)
83	Angie Low (2)	83	Joshua Lerner (3)	58	Kenneth A Carow (3)
84	Jarrad Harford (2)	84	Junbo Wang (3)	58	Lucio Sarno (4)
85	Rainer Haselmann (2)	85	Sheen Liu (3)	58	Mattias Nilsson (2)
86	Karl V Lins (3)	86	Yan He (2)	58	Micah S Officer (3)
87	Vasso P Ioannidou (3)	87	Andrea Buraschi (2)	58	Nadia Massoud (2)
88	Amit Seru (3)	88	Francis Breedon (1)	58	Oguzhan Ozbas (5)
89	Per Stromberg (3)	89	Qi Chen (1)	58	Per Stromberg (3)
90	Gang Hu (3)	90	Anna Kovner (3)	58	Rudiger Fahlenbrach (6)
91	Shane A Johnson (4)	91	Hai Lin (3)	58	S Viswanathan (4)
92	Stijn G Van Nieuwerburgh (4)	92	Paul A Gompers (2)	58	Sandy Klasa (3)
93	Nadia Massoud (2)	93	Morten Sorensen (2)	58	Sheen Liu (3)
94	Kewei Hou (2)	94	Victoria Ivashina (6)	58	Souphala Chomsisengphet (2)
95	Ji-Chai Lin (2)	95	Kai Li (3)	58	Sreedhar T Bharath (3)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 13: *(continued)*

	Betweenness		Eigenvector		Degree
95	Kevin Aretz (2)	96	Ulf Axelson (2)	58	Tarun Chordia (3)
95	Meghana Ayyagari (2)	97	Michael S Weisbach (1)	58	Terrance Odean (3)
98	Sandy Klasa (3)	98	Yan Leung Cheung (3)	58	Vikram K Nanda (4)
99	Isil Erel (3)	99	Rudiger Fahlenbrach (6)	58	W Scott Frame (3)
99	Reena Aggarwal (2)	100	Gregory B Van Inwegen (1)	58	Wei Jiang (3)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of papers written in our dataset.

Table 14: Most central researchers in the social network of informal collaboration in the early subsample (1998-200) - rank 26 through 100

	Betweenness		Eigenvector		Degree
26	Jeff Fleming (2)	26	Henri Servaes (11)	25	Kenneth R French (18)
27	Charles Cao (2)	27	Vojislav Maksimovic (6)	27	Kent L Womack (4)
28	Steven L Jones (2)	28	Tim Loughran (13)	28	Jeremy C Stein (20)
29	Robert C Nash (2)	29	Franklin Allen (21)	28	Maureen O'Hara (13)
30	Gregory F Udell (15)	30	Stewart C Myers (9)	28	Robert W Vishny (16)
31	Ivo Welch (8)	31	Mark Mitchell (13)	28	Tim Opler (14)
32	B Espen Eckbo (4)	32	Manju Puri (7)	32	D Bruce Johnsen (1)
33	Hamid Mehran (4)	33	Kent Daniel (11)	32	Edward J Kane (17)
34	John R Graham (7)	34	Michael S Weisbach (10)	32	Narayan Y Naik (3)
35	Peter Bossaerts (8)	35	Ernst Maug (12)	35	Alon Brav (9)
36	Denis Gromb (9)	36	John Mr Chalmers (10)	36	Hamid Mehran (4)
37	Charles W Calomiris (15)	37	Jeffrey Wurgler (0)	37	Manju Puri (7)
38	Edward J Kane (17)	38	Eugene Kandel (6)	37	Philip E Strahan (9)
39	Yakov Amihud (24)	39	Roni Michaely (8)	37	Tim Loughran (13)
40	Franklin Allen (21)	40	Peter B Henry (1)	37	Yakov Amihud (24)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the

Table 14: *(continued)*

	Betweenness		Eigenvector		Degree
41	Bernard Dumas (4)	41	Michael J Barclay (11)	41	Gurdip S Bakshi (1)
42	Philip E Strahan (9)	42	S Viswanathan (10)	41	Steven N Kaplan (22)
43	Linda Goldberg (3)	43	Michael D Ryngaert (7)	41	Sugato Bhattacharyya (4)
44	Oliver Hansch (1)	44	Andy Naranjo (3)	44	Andrew W Lo (6)
45	Charles M Kahn (2)	45	K Geert Rouwenhorst (5)	44	B Espen Eckbo (4)
46	Lars Eo Svensson (2)	46	Terrance Odean (1)	44	David J Denis (19)
47	Paolo Angelini (1)	47	Anthony Saunders (6)	44	Jeff Fleming (2)
48	J Darrell Duffie (13)	48	David S Scharfstein (13)	44	Jeffrey L Coles (3)
49	Andrew W Lo (6)	49	Paul H Schultz (9)	44	Michael J Brennan (18)
50	Rebecca S Demsetz (6)	50	Tim Opler (14)	50	John Mr Chalmers (10)
51	Sugato Bhattacharyya (4)	51	James B Heaton (2)	51	Edith S Hotchkiss (6)
52	Mitchell A Petersen (20)	52	Gregory F Udell (15)	51	Richard S Ruback (8)
53	Roni Michaely (8)	53	Kent L Womack (4)	53	Campbell R Harvey (14)
54	Francois M Longin (0)	54	Nicholas C Barberis (6)	53	Matthew Spiegel (10)
55	Lemma W Senbet (8)	55	Gordon Hanka (2)	53	Oliver Hansch (1)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 14: *(continued)*

	Betweenness		Eigenvector		Degree
56	Narayan Y Naik (3)	56	Mahendrarajah Nimalendran (1)	53	Paul A Gompers (9)
57	Nagpurnanand R Prabhala (9)	57	Anil K Kashyap (14)	53	Rebecca S Demsetz (6)
58	Arnoud Wa Boot (5)	58	Chyhe Esther Kim (0)	53	Steven L Jones (2)
59	Jan Pieter Krahnen (2)	59	Naveen Khanna (1)	53	Zsuzsanna Fluck (3)
60	George J Benston (9)	60	Michael J Brennan (18)	60	Eric Ghysels (4)
61	Bruce D Grundy (14)	61	Bhaskaran Swaminathan (2)	60	Paul H Schultz (9)
62	Kristian Rydqvist (7)	62	S P Kothari (13)	60	Peter P Carr (7)
63	Ernst-Ludwig Von Thadden (7)	63	Harrison Hong (0)	60	Peter Tufano (4)
64	Kent L Womack (4)	64	William G Christie (11)	60	Randall Morck (3)
65	Jeffrey Pontiff (6)	65	Kose John (14)	65	Bernard Dumas (4)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of thanks in our dataset.

Table 14: *(continued)*

	Betweenness		Eigenvector		Degree
66	Kose John (14)	66	Charles Mc Lee (6)	65	Charles Cao (2)
67	Kenneth R French (18)	67	John Y Campbell (12)	65	David S Scharfstein (13)
68	David S Scharfstein (13)	68	Judith A Chevalier (7)	65	Jennifer N Carpenter (8)
69	Michael S Weisbach (10)	69	Gary B Gorton (15)	65	Raymond Kan (4)
70	Henri Servaes (11)	70	Benjamin C Esty (3)	65	Robert C Nash (2)
71	David A Hirshleifer (17)	71	Christopher C Geczy (3)	65	Vojislav Maksimovic (6)
72	Bruce D Smith (7)	72	David T Brown (16)	72	Brad M Barber (10)
73	Hendrik Bessembinder (9)	73	Per Stromberg (2)	72	David A Hirshleifer (17)
74	Kenneth J Singleton (9)	74	Leslie M Marx (3)	72	Kose John (14)
75	Richard S Ruback (8)	75	Harry Deangelo (10)	72	Mark Grinblatt (9)
76	Edward Nelson (1)	76	Douglas W Diamond (11)	72	Owen A Lamont (6)
77	James T Moser (5)	77	Siew Hong Teoh (1)	72	Paolo Fulghieri (3)
78	Alon Brav (9)	78	Tarun Chordia (2)	72	R Glenn Hubbard (6)
79	Tim Loughran (13)	79	Richard H Thaler (5)	79	Ravi Jagannathan (14)
80	Michael L Lemmon (5)	80	Thomas J Chemmanur (3)	80	Chester S Spatt (9)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 14: *(continued)*

	Betweenness		Eigenvector		Degree
81	Campbell R Harvey (14)	81	Campbell R Harvey (14)	80	Jeffrey Pontiff (6)
82	Gurdip S Bakshi (1)	82	Mark Grinblatt (9)	80	Joshua Lerner (9)
83	Hyuk Choe (1)	83	Oliver Hart (9)	80	Robert E Whaley (3)
84	George Selgin (3)	84	Wayne E Ferson (25)	80	Russ Wermers (3)
85	Bruno Biais (8)	85	Matthew Spiegel (10)	80	Siew Hong Teoh (1)
86	Kees G Koedijk (0)	86	Todd C Pulvino (6)	80	Stuart C Gilson (8)
86	Mark D Flood (0)	87	Michel A Habib (6)	80	Venkat Subramaniam (1)
86	Ronald Huisman (0)	88	Michael L Lemmon (5)	88	Bhaskaran Swaminathan (2)
86	Ronald J Mahieu (0)	89	Joel F Houston (4)	88	Christopher M James (15)
90	Paul A Gompers (9)	90	Donald B Keim (4)	88	Ernst Maug (12)
91	Robert R Grauer (0)	91	Tj Wong (0)	88	Harry Deangelo (10)
92	Michael J Barclay (11)	92	Ravi Jagannathan (14)	88	Michael J Barclay (11)
93	D Bruce Johnsen (1)	93	Ananth Madhavan (17)	88	Suresh M Sundaresan (6)
94	Richard J Sweeney (0)	94	Theo Vermaelen (4)	88	Tj Wong (0)
95	Bert Scholtens (0)	95	Peter Tufano (4)	95	Carlos P Maquieira (0)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 14: *(continued)*

	Betweenness		Eigenvector		Degree
96	Neal M Stoughton (3)	96	Narayan Y Naik (3)	95	Eugene Kandel (6)
97	Owen A Lamont (6)	97	Raymond Kan (4)	95	Lance Nail (0)
98	Dale Henderson (4)	98	Christopher M James (15)	95	Marc L Lipson (12)
99	Chester S Spatt (9)	99	Robert F Stambaugh (9)	95	Mitchell A Petersen (20)
100	Matthew Spiegel (10)	100	Jarrad Harford (7)	95	Randall S Kroszner (5)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of thanks in our dataset.

Table 15: Most central researchers in the social network of informal collaboration in the late subsample (2009-2011) - rank 26 through 100

	Betweenness		Eigenvector		Degree
26	Ronald W Masulis (23)	26	Isil Erel (3)	26	Stijn G Van Nieuwerburgh (9)
27	Kai Li (12)	27	S Viswanathan (20)	27	Kj Martijn Cremers (11)
28	Tarun Chordia (11)	28	Alok Kumar (5)	27	Kose John (21)
29	Andrew Metrick (23)	29	Stewart C Myers (21)	29	Bernard Dumas (29)
30	Steven Ongena (22)	30	Lauren H Cohen (17)	29	Campbell R Harvey (29)
31	Martin F Grace (6)	31	Jeffrey Wurgler (21)	31	John Y Campbell (41)
32	Henrik Cronqvist (9)	32	J Darrell Duffie (40)	32	Amiyatosh K Purnanandam (12)
33	William L Megginson (13)	33	Massimo Massa (12)	32	Ralph Sj Koijen (7)
34	Holger Spamann (3)	34	Sreedhar T Bharath (18)	32	Zhi Da (6)
35	Andrei Shleifer (42)	35	Murillo Campello (18)	35	Alok Kumar (5)
36	Richard Roll (8)	36	Alon Brav (15)	35	David A Hirshleifer (22)
37	Philip E Strahan (30)	37	Raghuram G Rajan (18)	35	Rudiger Fahlenbrach (10)
38	Sheridan Titman (37)	38	Antoinette Schoar (31)	38	Robin Greenwood (12)
39	W Scott Frame (4)	39	Yakov Amihud (39)	39	Jay R Ritter (33)
40	Murray Carlson (8)	40	David S Scharfstein (24)	39	Mitchell A Petersen (43)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the

Table 15: *(continued)*

	Betweenness		Eigenvector		Degree
41	Jeremy C Stein (67)	41	Luigi Zingales (26)	41	Amir Sufi (21)
42	Lucio Sarno (3)	42	Adriano A Rampini (18)	42	Per Stromberg (24)
43	Vladimir Atanasov (4)	43	Tobias J Moskowitz (20)	43	John R Graham (21)
44	Bernard S Black (11)	44	Andrew Metrick (23)	43	Murray Carlson (8)
45	Fabio Panetta (6)	45	G Andrew Karolyi (28)	45	Jie Cai (4)
46	Chen Lin (0)	46	Augustin Landier (8)	46	Dimitry Livdan (9)
47	Xavier Gabaix (27)	47	David A Matsa (4)	46	Heitor W Almeida (24)
48	Kj Martijn Cremers (11)	48	Juhani T Linnainmaa (7)	46	Ilya A Strebulaev (15)
49	Jie Cai (4)	49	Dimitry Livdan (9)	49	Henrik Cronqvist (9)
50	Jeffrey H Harris (0)	50	Campbell R Harvey (29)	49	Malcolm P Baker (30)
51	Stefano Neri (1)	51	Lubos Pastor (33)	49	Michael W Brandt (22)
52	Jordi Gali (9)	52	Morten Sorensen (18)	49	Patrick Bolton (29)
53	Sumit Agarwal (5)	53	Jack Bao (3)	53	Bruce I Carlin (6)
54	Rajesh K Aggarwal (8)	54	Ilya A Strebulaev (15)	53	Kai Li (12)
55	Adrian Pagan (6)	55	Nittai K Bergman (6)	53	Victoria Ivashina (14)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 15: *(continued)*

	Betweenness		Eigenvector		Degree
56	Christian T Lundblad (9)	56	John H Cochrane (30)	56	Franklin Allen (36)
57	S Viswanathan (20)	57	Rudiger Fahlenbrach (10)	56	Lu Zhang (12)
58	Murillo Campello (18)	58	Todd A Gormley (11)	56	Mara Faccio (18)
59	David A Hirshleifer (22)	59	Per Stromberg (24)	56	Murillo Campello (18)
60	Gregory F Udell (14)	60	Michael Faulkender (16)	56	Steven N Kaplan (30)
61	Tim Bollerslev (11)	61	Avanidhar Subrahmanyam (21)	61	Haitao Li (3)
62	Amit Seru (14)	62	Patrick Bolton (29)	61	Sudheer Chava (6)
63	Heitor W Almeida (24)	63	Michael S Weisbach (31)	63	Alexander W Butler (11)
64	Mark S Seasholes (16)	64	Toni M Whited (20)	63	Henri Servaes (15)
65	Wei Jiang (15)	65	Clifford G Holderness (12)	63	Lubos Pastor (33)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of thanks in our dataset.

Table 15: *(continued)*

	Betweenness		Eigenvector		Degree
66	Alexander W Butler (11)	66	Sheridan Titman (37)	66	Anthony Saunders (16)
67	Hendrik Bessembinder (10)	67	Dirk Jenter (20)	66	Clemens Sialm (15)
68	Mattias Nilsson (0)	68	Mark T Leary (4)	66	Lauren H Cohen (17)
69	Motohiro Yogo (23)	69	Kj Martijn Cremers (11)	69	Gustavo Manso (8)
70	Paul Brockman (7)	70	Christopher A Hennessy (18)	69	Lorenzo Garlappi (14)
71	Shane A Johnson (10)	71	Adam C Kolasinski (8)	69	Lucian A Bebchuk (11)
72	Bernard Dumas (29)	72	Hui Chen (6)	69	Peter Tufano (13)
73	Gary B Gorton (12)	73	Anthony Saunders (16)	73	Geert Bekaert (12)
74	Chunchi Wu (2)	74	Philip Bond (16)	73	Michael S Weisbach (31)
75	Alex Edmans (25)	75	Holger M Mueller (12)	73	Wei Jiang (15)
76	J Darrell Duffie (40)	76	John Y Campbell (41)	76	Amit Seru (14)
77	Karl V Lins (9)	77	Heitor W Almeida (24)	76	Iftekhar Hasan (8)
78	John R Graham (21)	78	Anil K Kashyap (15)	76	Itay Goldstein (18)
79	Richard Stanton (6)	79	Amit Seru (14)	76	Luigi Zingales (26)
80	Maureen O'Hara (19)	80	Wei Jiang (15)	76	Sreedhar T Bharath (18)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 15: *(continued)*

	Betweenness		Eigenvector		Degree
81	Eduardo S Schwartz (8)	81	Jiang Wang (16)	76	Toni M Whited (20)
82	Sreedhar T Bharath (18)	82	Ralph Sj Koijen (7)	82	Maureen O'Hara (19)
83	Mark J Flannery (22)	83	Peter M Demarzo (26)	83	Berk A Sensoy (9)
84	Per Stromberg (24)	84	Philip E Strahan (30)	83	Jorg Rocholl (6)
85	Lucian A Bebchuk (11)	85	Kose John (21)	85	Eduardo S Schwartz (8)
86	Souphala Chomsisengphet (1)	86	Richard Roll (8)	85	Guofu Zhou (5)
87	Alok Kumar (5)	87	Michael W Brandt (22)	85	Hendrik Bessembinder (10)
88	Hong Liu (6)	88	Yuhai Xuan (3)	85	Jacob S Sagi (25)
89	Bas Jm Werker (12)	89	Harry Deangelo (18)	85	Josef Zechner (16)
90	Geraldo Cerqueiro (2)	90	David A Hirshleifer (22)	85	Jules H Van Binsbergen (5)
91	R David Mclean (6)	91	Simon Gervais (13)	85	Philip E Strahan (30)
92	Javier Suarez (14)	92	Uday Rajan (15)	85	Richard Stanton (6)
93	Luc Renneboog (2)	93	David J Thesmar (5)	85	Tobias J Moskowitz (20)
94	Warren Bailey (12)	94	Pietro Veronesi (12)	85	Wayne E Ferson (28)
95	Alexander Michaelides (1)	95	Jeffrey Zwiebel (16)	95	Narayan Y Naik (8)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to

Table 15: *(continued)*

	Betweenness		Eigenvector		Degree
96	Laura T Starks (27)	96	Gordon M Phillips (17)	95	Naveen D Daniel (6)
97	Adlai J Fisher (9)	97	Henrik Cronqvist (9)	95	Vikas Agarwal (9)
98	Robert Deyoung (18)	98	Christa Hs Bouwman (2)	98	David J Thesmar (5)
99	Zhi Da (6)	99	Atif R Mian (12)	98	Jeffrey Wurgler (21)
100	Randall Morck (18)	100	Greg Nini (4)	100	Efraim Benmelech (7)

Notes: Table lists top researchers in the network in terms of betweenness centrality, eigenvector centraliy and degree (neighbor count). Betweenness centrality of a researcher in the social network of informal collaboration is the probability that she is on the shortest path between any two other nodes (equation 7). Eigenvector centrality of a researcher in the social network of informal collaboration is the weighted count of her network neighbors, where the weights correspond to the neighbors' eigenvector centrality (equation 9). Both centralities were calculated using the largest connected network component. Numbers in parentheses indicate the number of thanks in our dataset.