Informal Contacts in Hiring: The Economics Job Market *

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August 13, 2018

We demonstrate the importance of 'social connections' in the labor market using a novel data set where we study the placement outcomes of doctoral students in Economics. We show that a PhD adviser's connectedness in the co-author network matters for her student's academic placement. An adviser's connectedness is measured by her Eigenvector centrality rank in the co-author network defined by more than 100,000 coauthored research articles. Students of more connected advisers obtain a better initial placement compared to students of less connected advisers. We identify the impact of adviser connectedness via *changes* in the centrality of the adviser's co-authors in a model with adviser-fixed effects. Additionally, we use the deaths of faculty members as an exogenous shock to show that the probability of a student being placed at a particular department reduces when the collaboration intensity between the student's school and that department decreases due to the death. Our results contain a more general insight for any labor market with information frictions - even indirect connections can significantly affect job market outcomes.

Keywords: Placement, academic labor market, social network, referrals

JEL Classification: A11, D83, J44, J64

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1 Introduction

The Economics labor market is organized annually by the American Economic Association with graduate students, their advisers and hiring institutions as market participants (Coles et al., 2010). Matching students to universities remains imperfect due to, inter alia, asymmetric information about the quality of the applicant. Reference letters and phone calls from the adviser(s) reduce these asymmetries (Athey et al., 2016; Colander, 1997).[1] Since an adviser can reduce the information asymmetry about the quality of her students in her academic network[2], we expect that better 'connected' advisers are able to reduce this information asymmetry more than less connected advisers. We test the hypothesis that PhD students of well connected advisers obtain better first placements than those of less connected advisers in the academic market for Economics graduates. We define adviser connectedness as the Eigenvector centrality rank of the adviser in the collaboration frequency weighted network of co-authors in the field of Economics, and we use the Tilburg University Economics ranking to judge the quality of a student's placement university. Eigenvector centrality measures not just 'connectedness' in terms of direct connections (number of co-authors), but also allows for indirect connections to influence connectedness. For example, if an adviser's co-author becomes more connected then this adds to the connectedness of the adviser as well, and this could potentially influence the placement of her students.[3]

The contribution of this paper can be separated into three parts. Oyer (2006) points out that the first placement of graduate students has a significant impact on their careers. Thus, first and foremost, our research is important for graduate students since it demonstrates another channel through which an adviser can influence student placement. The role of the adviser has also been explored by Krueger and Wu (2000), who report a correlation between the subjective prominence of the letter writer and student placement. We are also able to confirm that 'prominence' (which we in contrast equate with the Euclidean index[4] of citations) matters, but it does not account completely for the impact of adviser

[1] For example, Colander (1997) writes that "Recommendations from important people are extremely important" and "Informal contacts - and phone calls by your advisers and friends - are important".

[2] One other example of using social networks to reduce information asymmetry is given by Baruffaldi et al. (2016), who show that PhD students who obtained their Master's degree at an affiliation of their adviser's co-author are more productive than PhD students coming from a university to which their adviser has no links.

[3] Eigenvector centrality is the weighted sum of the Eigenvector centralities of the immediate neighbors, where the weights correspond to the neighbors' Eigenvector centralities. The idea behind this measure is that people connected to more connected individuals are themselves more connected. This has been shown to be informative in various settings. Cruz et al. (2017) recently show that politicians who are more Eigenvector central in a network of families receive higher voter turnout. Similarly, Calvó-Armengol et al. (2009) show that equilibrium efforts in networks are proportional to a variant of the Eigenvector centrality, and Banerjee et al. (2013) show that the Eigenvector centrality of the first-informed individual predicts how fast information spreads in a social network. A further discussion of this measure is in section 4.3.

[4] The Euclidean index of citations is the Euclidean sum of publications represented by their citation stock for any given year,

connectedness. We show that even after controlling for prominence, the connectedness of the adviser matters for her students' placement.

Secondly, though our results are for a unique job market, we are confident that our results offer two relevant insights for the general labor market as well. One, owing to our unique data set we are able to demonstrate the importance of even indirect connections in job search. For example, though an adviser may not have a co-author at a given University, she may still be able to put in a good word for her student there if her coauthor has a co-author in that university. This distinguishes our paper from those in the literature on referrals who only look at direct links (Kramarz and Skans, 2014; Burks et al., 2017) - current employees referring a worker in their current workplace. While these papers establish the value of direct connections, they do not speak about which workers are more 'connected' than others, and whether this matters for job seekers. For example, a link with a worker who has worked in several firms may be more valuable to a job seeker than a link with a worker who has worked at only one firm because the former has connections with more employers[5]. It is important to understand how connectedness impacts job outcomes because this could have repercussions on the distribution of income. People close to more connected workers may have higher incomes than people with fewer connections, and this could perpetuate. Two, by focusing on the Economics job market where there is little information asymmetry about new job openings (thanks to Job Openings for Economists and other web pages), we provide some supportive evidence to show that network connections can be used to reduce information asymmetry about the quality of the job candidate, and this helps applicants get better jobs. This is an important distinction from the literature on job search (Granovetter, 1973; Bayer et al., 2008), which is usually unable to distinguish between two channels via which social networks usually affect labor market outcomes: learning about new job openings versus reducing information asymmetry about the job candidate[6].

A final contribution of this paper is the novel data set we create for our analysis, which was collected from various first and second hand sources. Our sample consists of 2790 Economics students who obtained their PhD from 137 different North American universities during the academic years 2000/2001,

as proposed by Perry and Reny (2016).

[5]Assuming of course that the worker left his past employers on good terms! Also, while we realize that the general labor market does not have an 'adviser' who places workers, at its heart, this paper is about pointing out that more connected people may be more valuable in a job search. This message will be true for any labor market with information frictions.

[6]There are, however, theoretical arguments highlighting the result that referrals by current employees can diminish information problems arising from the fact that employers do not know worker quality perfectly (Montgomery, 1991; Burks et al., 2017; Dustmann et al., 2016; Hensvik and Skans, 2016). Furthermore, while economics graduates know about most of the job openings, they may not have other relevant information regarding these openings such as the work environment at the prospective department. An adviser can help reduce these information asymmetries as well. Thus, our focus on channel side is a reduction in information asymmetry - this could be regarding student quality or about other variables which can affect the match quality.

2001/2002, and 2002/2003. Our data originates from the Journal of Economic Literature, which, each December publishes a list of new Economics graduates of North American universities. For each student, we find the adviser and the first placement from various sources including department websites, direct emails to departments, students' CVs and the genealogy project of the RePEc database. The social network of coauthors is constructed using 114114 publications in 408 journals.

We show that advisers who are more connected (have a better eigenvector centrality rank in the network of coauthors) place their students at better ranked universities compared to those who are not as well connected. Obviously, the connectedness of the adviser in the network of co-authors is endogenous. We identify the impact of adviser connectedness by using the *changes* in the connectedness of the adviser's co-authors (in a model with adviser-fixed effects) as an instrument. The identifying condition here rests on the following ideas. One, we control for time-invariant unobserved adviser characteristics via adviser fixed effects. Two, *changes* in the connectedness of the adviser's co-authors *in the year of a student's placement* would be difficult to anticipate (and therefore use strategically) for both the student and the adviser. Therefore, it can be thought of as an exogenous variable which changes adviser connectedness in the year of placement, and affects student placement only via this channel. A deeper discussion of the critical empirical challenges and our identification strategy is presented in section 3.

In section 5.2, we provide additional evidence to support our hypothesis that an adviser's connectedness matters for her student's placement. We use the death of economists as an exogenous shock which affects the 'distance'[7] between an adviser and a department, and we show that an increase in this social distance negatively affects the probability of the adviser placing her student at that department. Finally, in section 5.3, we provide supportive evidence to argue that the channel through which an adviser's connectedness affects her student's placement is that it helps the hiring university screen better by reducing information asymmetry regarding the student's quality.

2 Literature

Social networks and informal connections help a worker in finding a job in two main ways. One, by giving the worker information about new job postings (Granovetter, 1973; Boorman, 1975; Calvó-Armengol, 2004; Calvó-Armengol and Zenou, 2005). Two, by reducing the information asymmetry between the

[7]The shortest path between the adviser and the department in the co-author network.

worker and the employer about the worker's ability[8] (Montgomery, 1991; Burks et al., 2017; Dustmann et al., 2016). However, studies which look at the former channel - like those which study the impact of neighborhoods and other 'local' networks on job search, often cannot distinguish between these two effects. For example, Bayer et al. (2008) find that individuals residing on the same block are more likely to work together. However, it is not clear if this is simply because neighbors learn from each other about new job openings, or if they actually recommended them. In contrast, we study the Economic job market where the job seekers have almost full information about all the job openings. This is because most job openings are posted on one web page - Job Openings for Economists (JOE). Thus, the setting in our paper is particularly conducive to studying how much social connections can help by reducing information asymmetry about the quality of the job candidate.

The literature on referrals studies how firms can screen better when they use referrals from their current workers to hire new employees. Montgomery (1991) establishes that there are gains from referral hiring as employers can utilize recommendations from their productive workers to identify other productive potential workers. Hensvik and Skans (2016) directly test this empirically. Building on learning models, Dustmann et al. (2016) hypothesize that job search networks help reduce information deficiencies in the market and consequently referral-based job searches lead to better matches. The authors proceed to test the prediction empirically and show that referred workers initially earn higher wages. Few other studies have addressed this issue empirically. Burks et al. (2017) for example, show that referred workers are less likely to quit even though their productivity does not differ from that of non-referred hirings.

The literature on referrals makes clear that knowing a currently employed worker can increase the probability of landing a job at their current firm for a job seeker. However, the papers in the literature do not quantify the value of any given connection as compared to another. For example, if a job seeker has a link with two workers, which one is more valuable to the worker? Do they have the same value if the two workers work in similar firms in similar positions? Our paper contributes to the literature on job search by using a unique data set to map the network of connections to show a causal relationship between nodes which are more connected (as per network theory measures of connectedness) and job market outcomes of job seekers who have a link with these nodes. Furthermore, since we study the entire network of social connections, we are able to take into account the impact of indirect connections as well as those of direct links. For example, Kramarz and Skans (2014) look at the direct link between parent

[8] Nepotism and reciprocity are other possible channels.

and children and establish that this connection is important for the job market outcome of the children. Burks et al. (2017), Hensvik and Skans (2016) show that workers recommended by the current employees are often a better match for the firm. However, if a worker knows about a job opening at her previous employer or if a worker knows a friend who is employed in a different firm, then these papers will not be able to capture how the worker can use this information to help a job seeker get the job. For this, one would have to know the entire network of work-links amongst all workers. Some studies do try to infer networks from available data. For example, Dustmann et al. (2016) proxy a referral hire by the share of workers in the firm with the same ethnicity as the applicant. However, these inferences are imprecise. In contrast, our data allows us to precisely link economists whenever they have published a research article.

The literature on the Economics job market is relatively small. We know of no other papers which study the importance of the connectedness of the adviser for the placement of the student. In addition, most papers establish interesting correlations without showing causality. For example, Athey et al. (2016) look at graduates from the top PhD programs in the USA to show that first year (graduate school) grades in core courses of Microeconomics and Macroeconomics are significantly related to better job placement. They also report that the quality of the undergraduate institution of the student also affects the quality of first job. Krueger and Wu (2000) show that the 'prominence' (measured in an admittedly subjective manner) of the recommendation letter writer helps student placement. Smeets et al. (2006) show that market does not rely completely on the reputation of the PhD granting university since they find that often the top graduates of very good (but not elite) programs outperform average graduates of elite programs in terms of initial placement. Gallet et al. (2005) test a multi-market strategy in the Economics Job Market and confirm its predictions regarding cyclicity: "in the bust market, graduates of elite schools shifted their search strategies to include weaker academic institutions, while graduates of lower-ranked schools shifted their applications away from academia and toward the business sector." To avoid this kind of selection bias was one of the reasons why we chose to work with data from the years before the financial crisis for our study. Baruffaldi et al. (2016) study the use of academic networks (science and engineering students only) in the hiring of PhD students and its impact on student productivity. They show (without claiming causality) that PhD students hired from masters programs at affiliations from which the adviser of the PhD student draws co-authors have, on average, a higher productivity compared to students hired from universities to which their adviser has no links. Unlike our study though, this study is unable to indicate the importance of the centrality of the student's masters professors on their PhD program placement.

3 Empirical Issues and Identification Strategy

Our objective is to identify the effect of adviser connectedness on student placement. Additionally, we would like to provide supportive evidence to show that the channel through which adviser connectedness helps students on the job market is by reducing information asymmetry about the student's quality (via informal phone calls/emails). Naturally, there are several endogeneity issues we need to contend with.

Consider the problem of identifying the impact of the adviser's connectedness on student placement (we discuss issues with identifying the channel through which connectedness affects placement in section 5.3). An adviser's connectedness in the network of co-authors is not exogenous. Advisers who are more productive, at better universities or are older are more likely to be better connected. Therefore, a simple regression of student placement on adviser connectedness may pick up the impact of these variables rather than that of connectedness. Furthermore, while we can mitigate the above effects by controlling for the adviser's publication record, university and seniority (which we do), there might be unobserved variables which affect both adviser connectedness and student placement. Ideally, we would like a variable which exogenously shifts adviser connectedness but does not affect student placement through any other channel.

Our strategy is to use placement data over several years and identify the impact of adviser connectedness on student placement via *changes* in the connectedness of the adviser's co authors in a model with adviser fixed effects (to control for unobserved adviser characteristics). The connectedness of an adviser's co-authors' can change when her co-authors start new projects with new co-authors. This affects the centrality score of the adviser as well, and while the centrality *level* of an adviser's co-authors is endogenously determined, our identifying assumption is that the *change* in the connectedness of an adviser's co-authors *in the year of placement of the student* is not anticipated, and is therefore not strategically used by either the adviser or her students for better placement. Thus, we believe that this variable does not directly affect the placement of the adviser's students except to the extent that it changes the adviser's connectedness in the year in which the student is on the job market. We include adviser fixed effects in our regressions to make sure that there are no unobserved adviser characteristics biasing our coefficients. This strategy works as an IV for all advisers who place graduate students in more than one year in our data set.

Additionally, we show results without adviser-fixed effects (since this allows us to use more data[9]). The identification assumption is stronger in this case though. The underlying identifying assumption in the model without adviser fixed effects is that after controlling for the adviser's publication record, experience, gender and affiliation, the only channel through which the *level* of connectedness[10] of an adviser's co authors' affects student placement is by affecting the connectedness of the adviser.

Now, we discuss more deeply the specific channels which could bias our results, and how our identification strategy assuages these concerns. First, there are many unobserved characteristics of the adviser which could be correlated with both adviser connectedness (even with changes in adviser connectedness) and student placement. For example, one may argue that better/smarter advisors are more likely to increase their network in any given year via new collaborations. Or, a different channel could be that more 'helpful' advisers are more likely to write papers with their students, and younger economists are likely to engage in more collaborative projects. Thus, being helpful may affect the change in connectedness of any adviser (via changes in the centrality of their ex student-coauthors), and also affect their student's placement in any given year. We address all such concerns about unobserved adviser characteristics biasing our coefficients by including adviser fixed effects in our models. Additionally, we include controls for several observed adviser characteristics like publication quality and experience which are not time invariant, and could influence student placement.

Next, we discuss if unobserved student quality and assortative matching could bias our results. We don't have sufficient controls for an important variable which affects student placement - student quality. This could bias our estimates if good students are more likely to match with more connected advisers. If this were the case then good placements will be because of high student quality and not because of the connectedness of the adviser. For this issue, we have the following argument. Our identification strategy breaks down only if there is an unobserved variable which affects student-adviser matches and is simultaneously correlated with the change in the centrality of the adviser's co-authors in the year in which the student gets placed. However, we believe that it is hard for students (and advisers) to anticipate the change in connectedness[11] of their adviser's co-authors' *in the year of their placement*. Thus, we argue that the change in the centrality of the adviser's co-authors affects student placement only via

[9] Advisers who place students in only one year (between 2000/01 and 2003/04)) were obviously excluded from the model with adviser-fixed effects.

[10] Note that this considers only the level of connectedness (in the model without adviser fixed effects) of the adviser's co-authors, not the change in the level of connectedness since we don't have adviser fixed effects.

[11] Students may know the approximate *level* of their adviser's connectedness in the year in which they choose their adviser but it would be quite difficult to anticipate the precise *change* in connectedness of their adviser's co-authors in their expected future graduation year.

(exogenously) changing the adviser's connectedness.

Another counter argument could be that of clustering. As an example, the clustering argument would say the following: *helpful advisers have helpful co-authors and helpful co-authors are more likely to have changes in connectedness (because more people are willing to work with them)*. However, the impact of clustering must die down with distance from the adviser. That is, the probability of sharing a quality reduces with distance. As a robustness check we look at the co-authors of an adviser's co-authors (i.e. the second neighbors of the adviser) and then take their connectedness as IV for adviser connectedness in a model with adviser fixed effects.

Before we move on to describe a data issue we face, we would like to point out that despite our best efforts there are some remaining channels which may bias our results. We leave it to the judgment of the reader to determine how big these effects may be. One example of such a channel would be if a subfield suddenly became popular. If both the adviser and her student work in this subfield, then this will affect both the change in the connectedness of the adviser (more papers will be written in this subfield which will mean more collaborations), and the ranking of the student's placement (more universities may be interested in hiring in the newly popular subfield). We wish to make two points regarding this channel. One, we control for field fixed effects so the above channel can only work for smaller subfields. Two, for the above argument to bias our coefficients, the subfield would have to suddenly become popular *within* the short time period of our data set (1999-2004).

A significant data issue we face is that of sample selection. Due to data limitations and our identifying restrictions, we lose data points from the initial sample size of 2790 . The main restrictions are - a) we can only consider students who were placed in Tilburg ranked departments, b) we can only consider those students whose adviser placed students at Tilburg ranked departments in multiple years between 2000 and 2003 (to employ adviser fixed effects), and c) we study only those students for whom we have both placement and adviser information. The final sample size is 277 students (about 10 percent of the original sample). Losing a large fraction of our student data set can lead to selection bias in our estimated coefficients. While we have no strong arguments to negate the effect of this data issue, we would like to make the following observation about the probable direction of bias. Table 1 shows that the final sample size is biased towards higher-ranked institutions: about 47% of all students in the initial dataset (of 2790 students) received their PhD from a university ranked 30 or better in the year of their graduation. This share increases to about 74% in the final sample size we use for our regressions. We expect that adviser connectedness matters more for students who are not from top schools. This is because students from better ranked universities usually reduce information asymmetry about their quality via publications before the job market, and by presenting their work at top conferences (this also gives them a chance to network). Therefore, it is possible that our estimate of the impact of adviser connectedness on student placement is a conservative one.

Table 1: Comparison of initial and final dataset.

	Initial		Final	
	Number	Share (in %)	Number	Share (in %)
Ranks 1-30	1313	47.06	207	74.73
Ranks 31-100	688	24.66	55	19.86
Ranks 101-300	614	22.01	13	4.69
Other	175	6.27	2	0.72

Notes: Table lists number of students and share of total by PhD school group for the initial and the final dataset. PhD schools are grouped according to the rank in the student's year of graduation. Students of 6 PhD schools without rank were categorized together with "Other".

Finally, we also show that co-author networks matter for student placement in a simpler way. Suppose the distance between a department and an adviser is defined as the shortest path in the co-author network between the adviser and any faculty member at the department. We use the death of economists (anywhere in the co-author network) as an exogenous shock which affects the social distance between an adviser and different departments negatively[12]. We then ask whether an increase in the social distance due the death of economists affects the probability of the adviser's student getting placed in the department. Examining the effect of deceased individuals on their local network is a popular identification strategy in the study of social networks (Azoulay et al., 2010; Fracassi and Tate, 2012; Oettl, 2012; Azoulay et al., 2015). There are 29 researchers who passed away during the 1999/2000-2003/2004 period[13]. Table 11 in the appendix gives an account of these researchers along with their date of death.

[12] The death of an economist could increase the distance between an adviser and a department by breaking the shortest co-author path the adviser had to that department.

[13] We let the period start one year earlier than our student sample because vacancies from researchers that passed away in the year are likely to not be filled up so soon.

4 Data

4.1 Doctoral Dissertations in Economics

Lists of doctoral students receiving their PhD from an Economics-related faculty in the US and Canada are published annually in the December issue by The Journal of Economic Literature (JEL). These dissertations are, with few corrections and additions as well as different information, also available from EconLit. We focus on four academic years, namely 2000/2001, 2001/2002, 2002/2003, and 2003/2004. The information from both the JEL lists and EconList include the JEL field of their dissertation along with the year in which they were awarded the PhD and the name of the PhD school.

We have information on 3483 students from 137 different schools. To obtain a more homogeneous set, we restrict the sample to large fields only. That is, we exclude students whose dissertation were classified as belonging to a JEL general category with less than 150 graduate students in total.[14] In a third step, we remove 300 students that belong to JEL general category "Q" (Agricultural and Natural Resource Economics; Environmental and Ecological Economics) because the labor market for agricultural Economists is different from the rest of Economics. After this process we are left with 2790 students, whose distribution of year and JEL code is summarized in table 2.

Table 2: Crosstable by year and JEL code for all PhD students.

JEL Year	C	D	E	F	G	I	J	L	O	All
2000	21	34	40	49	34	30	39	33	71	351
2001	50	76	82	99	95	55	78	67	94	696
2002	39	82	79	88	96	53	71	63	112	683
2003	40	94	89	85	80	68	64	54	95	669
All	150	286	290	321	305	206	252	217	372	2399

Notes: Table lists numbers of graduated PhD students from North American universities for the academic years 2000/2001, 2001/2002, 2002/2003, and 2003/2004 by Journal of Economic Literature general category. Students belonging to JEL general categories with less than 150 students and from JEL general category Q are excluded.

We obtain information about the student's advisers from four sources. First, we use the genealogy

[14] These small general categories are "A" (General Economics and Teaching, 2 students), "B" (History of Economic Thought, Methodology, and Heterodox Approaches, 10 students), "H" (Public Economics, 125 students), "K" (Law and Economics, 26 students), "M" (Business Administration and Business Economics; Marketing; Accounting; Personnel Economics, 45 students), "N" (Economic History, 41 students), "P" (Economic Systems, 68), "R" (Urban, Rural, Regional, Real Estate, and Transportation Economics, 74 students) and "Z" (Other Special Topics, 2 students).

database of the Research Papers in Economics (RePEc) project.[15] Second, we obtain adviser information from academic departments, either through public sources in the form of websites, or privately through direct emails.[16] Third, we collect CVs of the students themselves. The fourth source includes various online sources such as academic tree or Mathematics Genealogy Project. Using the Scopus database we compute the Euclidean index of citations for each year for each adviser as a measure of adviser productivity. Perry and Reny (2016) show that, unlike other indices (such as the h-index), this index has desirable properties if one is interested in combining citation stock and publication count.

Table 9 in the appendix ranks advisers by number of graduating students in 2000-2004 period. The ranking is lead by Daron Acemoglu having a total of 23 PhD students (which includes co-supervised students). He is followed by Andrej Shleifer (20 students) and Roger Betancourt (18 students). A data issue we face is that a fraction of the advisers in our sample had only one of their students graduate in the 2000/2001-2003/2004 period. Figure 2 in the appendix shows that out of 1332 advisers, more than 650 advisers had only 1 student graduate in our time period, about 300 advisers had 2 students, and less than 180 advisers had 3 students graduating in this period. This implies that an analysis with adviser-fixed effects would have to use data from a subsample of students only. This will create a sample selection bias. Since we lose more students from lower ranked universities to this selection, and the impact of adviser connectedness should be higher for lower ranked universities,[17] we advise that our estimated impact of adviser connectedness on student placement be thought of as a conservative estimate. To use more data, we also report results from regressions without adviser-fixed effects. However, the identification condition needed in this regression is much stronger.

Finally, we estimate the gender of students and advisers based on their first name using the genderize.io database.[18] Out of the 1332 advisers, we estimate 151 to be female, which corresponds to a share of roughly 10%. The share of female PhD students is higher, with 1162 out of 2790 (28%).

[15] See https://genealogy.repec.org/ Information on advisers requires the existence of a RePEc account of the student.

[16] Of 131 contacted departments, 29 sent information, 17 declined to share these information and 10 do not have records from the period 1999-2004.

[17] This is because students from better ranked universities usually reduce information asymmetry about their quality via publications before the job market, and presenting their work at top conferences (this also gives them a chance to network).

[18] See https://genderize.io/.

4.2 Economics Job Market

Information on initial placements is available either through the student's CV or from their former departments directly.[19] Figure 4 in the appendix visualizes the hiring network for the students in our network. To measure the quality of the initial placement we convert the initial placement into placement ranks. We use the Tilburg Economics University Ranking, which, for each year, ranks Economics departments worldwide based on the weighted publication output in 70 Economics journals in the previous five years.[20] We use the affiliation rank in the year of the placement. Gaps of missing ranks for few years were interpolated linearly. Figure 3 gives an account of the distribution of ranks of the initial placements.[21]

Our analysis focuses on academic placements only. Out of the 2790 students in our sample, 782 (roughly 27%) initially went to a Tilburg-ranked institution. A further 202 PhD students were initially placed at universities that are not ranked in the Tilburg Economics Ranking in the year of placement. Students interested in a research career may not only go to universities, but to research-active financial institutions such as the International Monetary Fund (55 PhD students), the World Bank 28 PhD students), and various central banks (58 PhD students). Research intensive private companies (Cornerstone Research etc.) hired 25 students, while consulting firms hired another 22 students. We also note that the academic career is not the only possible career fresh Economics graduates want to pursue (Stephan, 2012; Conti and Visentin, 2015).

We augment our data with information about the 'tightness' of yearly job markets. We use yearly "Reports of the Director Job Openings for Economists" published in The American Economic Review,[22] which give an account of the number of openings per field (as defined by the JEL code). To measure tightness in a given year for a given field, we divide the supply of students in a field by the number of openings in that field:

$$\text{Tightness}_{tf} = \frac{Students_{zf}}{\text{Openings}_{tf}} \tag{1}$$

where z is the academic year starting in the second half of year t and f is the JEL code-defined field. That is, students finishing in the first half of a year are accounted to the previous year's job market. Clearly, a

[19] Not all universities give an account of their student's initial placement. We contacted all departments to share information. 31 sent placement information, 17 declined to share these information and 14 do not have records of that time. The remainder did not answer.

[20] For the ranking see https://econtop.uvt.nl/; for the methodology see https://econtop.uvt.nl/methodology.php.

[21] Estimations using the unweighted count of publications in these 70 journals do not alter the qualitative results. The likely reason is that the 70 Economics journals used to measure the weighted publication output are all very good journals.

[22] In particular, we use the reports by Hinshaw (2000, 2001, 2002, 2003) and Hinshaw (2004).

higher tightness ($Tightness_{tf}$) would indicate that the market is more 'difficult' for students in field f in year t (higher supply of students in that field compared to demand). In our analysis, we show that adviser connectedness matters more for her student's placement in years with higher tightness as compared to years with lower tightness.

4.3 Networks of Collaboration

Our variable of interest is adviser connectedness in the Economics co-author network. In a co-author network, nodes represent researchers, and a link exists between two nodes if the researchers have jointly published a full research article. Co-author networks have sparked great interest among Economists, starting with Eagly (1975) who describes "Economics Journals as Communications Network". More recently Goyal et al. (2006) have shown that Economics co-author networks since the 1990s have small-world properties, implying that communication is greatly facilitated by a few highly interlinked stars. Ductor et al. (2014) show that one's current local network has predictive value for one's future productivity.

To construct the co-author networks we consider 114114 publications indexed in Elsevier's Scopus database published in 408 journals between 1997 and 2005. Since our analysis covers the period up until 2004, we include co-author ties visible one year later (as the research project must have begun earlier). The set of journals from which we draw our co-author network is defined according to field-wise rankings in Combes and Linnemer (2010). We include every title that is ranked at least C in any field-wise ranking. In this network two researchers are connected when they have jointly published a paper, where the link weight corresponds to the number of joint publications. The idea behind the weight is that if a pair of researchers have published several papers as co-authors then they have a stronger connection compared to if they had worked together only once.

For each year $t (\in \{2000, 2001, 2002, 2003, 2004\})$ we construct the network using the publications published in all years $1996, 1997, \cdots, t, t+1$. We chose the network definition such that network variations comes from new connections and old connections are not disregarded. As the number of articles increased over time, the network grew too. In the earliest of our networks, the one for the year 2000, there are 30310 distinct researchers. The network for 2004 consists of 52538 distinct researchers.

Using the network we compute measures of connectedness for each node for each year. Eigenvector centrality is a measure of influence and defined as the weighted sum of the Eigenvector centralities of the network neighbors, where the weight corresponds to the neighbor's own Eigenvector centrality. The idea is that if one is connected to nodes that are themselves more connected then one is more connected. The centrality score is obtained as a fixed point. More formally, given the symmetric square matrix G (the so called adjacency matrix), whose entries G_{ab} indicate the strength of a connection between a and b, Eigenvector centrality $\mathrm{E}(a)$ for node a is formally defined as

$$\mathrm{E}(a) = \frac{1}{\lambda} \sum_{b \in G} g_{ab} \mathrm{E}(b) \tag{2}$$

The vector that solves n equations for n network nodes simultaneously is the eigenvector corresponding to G's largest eigenvalue. For technical reasons we only consider the network's giant component. This is the network's largest component where each node is interlinked to any other node by an uninterrupted series of links. Two nodes are said to be in two different components when there is no such path of links. While it is theoretically possible to compute centralities for each component, they are not comparable, as the computation takes into account the size of each component. The respective giant component for our analysis covers about one third of the overall network size. Finally, since the centrality scores only indicate the relative importance of different nodes, we convert the scores into ranks for nodes.

In the second part of our analysis we are interested in the connectedness of advisers with universities, rather than with other economists. We use the Hasselback Faculty Directories for Economics, Management and Finance to obtain information on faculty membership[23]. Faculty rosters for Economics exists for 2001/2002 and 2003/2004 academic years, for Management for the 2001/2002 academic year, and for Finance for the academic years 2000/2001, 2002/2003 and 2004/2005. The rosters include 14203 distinct faculty members which we could identify on Scopus (a pre-requirement to be in the co-author network). 6071 of the faculty members are also nodes in the co-author network.

[23] See http://www.jrhasselback.com/FacDir.html. The lists are sometimes called Prentice Hall Guide to Economics Faculty resp. Prentice Hall Guide to Finance Faculty individually.

5 Empirical results

5.1 Centrality rank and placement rank

We look at all those students in our sample for which the following three requirements hold: (1) the student was placed at a Tilburg-ranked institution, (2) the student's adviser is a member of the co-author network's giant component, (3) conditions (1) and (2) hold for at least one other student of the same adviser who graduated in a different placement year. Condition (3) is crucial for our identification strategy since want to use a model with adviser-fixed effects to obtain identification via *changes* in the centrality of the adviser's co-authors. Our final sample is called the 'adviser coauthor centrality sample', and it consists of 277 students.

For this sample, the summary statistics are presented in table 3, while table 10 (in the appendix) reports the relevant correlation coefficients. The mean placement in the year of the placement has rank 123.3, which for 2004 refers to the Economics departments of the Universities of Alicante, Exeter and Manchester. It ranges from rank 1 (Harvard University, in 2004) to rank 642. Figure 3 in the appendix presents the distribution graphically. Our variable of interest is the adviser's coauthors' mean Eigenvector centrality rank and this has a mean of 6425.1, ranging from 193 to 20930.[24] The average Euclidean Index of citations for the adviser is 301.7 and ranges from 1 to 2254. Adviser experience is measured by the number of years since the first indexed publication. This is 18 years on average, ranging from 4 to 45 years.

For our analysis, we estimate the following regression equation in an ordered logistic regression model[25]:

$$\begin{aligned} PlacementRank_{it} =& \beta_0 + \beta_1 AdvisersCoauthorsMeanEigenvectorRank_{it} + \\ & \beta_2 Gender_i + \beta_3 PhDSchoolRank_{it} + \beta_4 AdviserControls_{it} + \\ & \gamma_1 Adviser_i + \gamma_3 YearOfCompletion_i + \gamma_4 Field_i + \epsilon_{it} \end{aligned} \tag{3}$$

The outcome variable is the Tilburg rank of the placement of student i in year t. *AdvisersCoauthorsMeanEigenvectorRank*$_{it}$ is the mean Eigenvector centrality rank over all of student i's adviser's coau-

[24]The minimum rank equals 193 and not 1 as one might expect for two reasons. First, it's the average over all neighbor's centrality ranks, and secondly our ranks are relative to the entire population that makes up the network.

[25]Results of an ordered probit regression are qualitatively the same.

Table 3: Summary statistics in the adviser coauthor centrality sample.

	N	Mean	Median	Std.Dev.	Min	Max
Placement Rank	277	123.3	53	151.91	1	642
Adv. neigh. mean Eigenvector rank	277	6425.1	5504	4009.89	193	20930
Market tightness	277	0.295	0.287	0.142	0.094	0.866
School Rank	277	29.7	10	51.18	1	293
Adv. Euclidean Index	277	301.7	152	414.00	3	2554
Adv. experience	277	19.3	18	7.88	4	45

Notes: Placement Rank is the Tilburg Economics rank of a student's placement in the year of the placement. *Adv. neigh. mean Eigenvector rank* is the mean Eigenvector centrality rank of all coauthors of an adviser in the weighted coauthor network corresponding to the year of the placement. *Market tightness* for a field in a given year is the number of students graduating in that year in that field, divided by the number of AEA-reported job openings in that field in that year, where field is measured by JEL code (equation (1)). *PhD School Rank* is the Tilburg Economics rank of the PhD-awarding university in the year the student finished. *Euclidean Index* is the adviser's Euclidean index of citations in the year the student graduated. *Experience* is the number of years between an adviser's first publication and the year in which the student graduated.

thors in the weighted coauthor network for year t. We are interested in β_1. Note that since lower numbers indicate better ranks[26], we expect β_1 to be positive as this would indicate a positive relationship between adviser centrality and better placement. $Gender_i$ is a binary variable indicating a female student. We also have another gender control (*samesex*) which is a binary variable indicating that student and adviser have the same sex. $AdviserControls_{it}$ include the adviser's Euclidean index of citations in t, her experience and experience squared, because these values are time-variant. $PhDSchoolRank_{it}$ is the Tilburg Economics Department Rank of the PhD granting school of student i in year t. In a variation of the model we replace $PhDSchoolRank_{it}$ with university-fixed effects. In all specifications we cluster standard errors at the PhD granting University level to allow for unobserved heterogeneity as well as different group sizes[27]. Fixed-effects for the year of completion captures year-specific information. We also include fixed-effects for the student's field. Adviser-fixed effects control for unobserved adviser characteristics which could influence student $i's$ placement.

Table 4 presents results from an ordered logit regression model (regression equation (3)). In column (1), the adviser's neighbor's mean Eigenvector centrality rank is statistically significant and has the expected sign. We conclude that adviser's centrality matters for student placement. An improvement in

[26] Both the dependent variable $PlacementRank_{it}$ and the main explanatory variable $AdviserCoauthorMeanEigenvectorRank_{it}$ are ranks.

[27] Abadie et al. (2017) argue that standard errors must be clustered around a variable when there is selection bias in the sample on that variable. We definitely get more students from better ranked universities in our final sample (see Table 1).

the adviser's co-authors' average Eigenvector centrality rank by 1, results in a $e^{0.0000940} - 1 \approx 0.01\%$ better placement outcome, where 'better' refers to a better ranked department according to the Tilburg Economics ranking. A 0.01% improvement translates into $0.0001 * 642 = 0.064$ placement ranks. To put this into perspective, there are between 26,000 and 40,000 nodes in the yearly varying co-author networks, as nearly every node has a unique rank. Hence, the scope for rank change amongst an adviser's coauthors' is considerably large. An improvement in 100 ranks in the mean rank of an adviser's coauthors would result in a placement rank improvement of the adviser's student by approximately 6.4. The coefficient for female students and adviser-student relationships of same sex are negative but statistically insignificant. Hence there are no gender-effects in student placement. This is interesting in light of the recent finding of Gaulé and Piacentini (2017), according to whom Chemistry students tend to be more productive during their PhD and more likely to become a full professor later if their adviser is of the same gender.

In column (2) we control for the student's PhD granting university via PhD school fixed effects (as opposed to by the Tilburg Economics Department Rank in column 1). Despite the sharp decrease in degrees of freedom with a relatively low number of observations, our variable of interest remains statistically significant at conventional levels. In column (3) we remove adviser-fixed effects in order to gain observations. Previously omitted observations consist of student placements where the corresponding adviser had no students placed in academic institutions in multiple years. Our coefficient of interest remains positive and statistically significant.

We hypothesize that if informal contacts do matter for placements, then their value should increase with tighter market conditions. That is, the adviser's connectedness should play a stronger role in student placement in the years in which there is more competition for placement. To test this hypothesis we interact our variable of interest, the adviser's coauthors' Eigenvector centrality rank with market tightness. Table 5 presents regression results in a model where are our variable of interest is interacted with market tightness as defined in equation (1). As before, we include adviser-fixed effects, field-fixed effects and cluster standard errors around the PhD granting school, but unlike before, we do not control for placement year. This is because if we include year fixed effects then field and year fixed effects would completely absorb any market tightness variation. In column 2 we replace school rank with school-fixed effects, and in column 3 we drop adviser-fixed effects to gain more observations. In the first two models, Adv. neigh. mean Eigenvector rank × Market Tightness is statistically significant and has a positive sign. Thus, we confirm our hypothesis that an adviser's connectedness matters more when market conditions are tight.

A possible concern with our centrality regression is that of ‘clustering’. We use changes in the centrality of the adviser’s co-authors to identify the impact of the adviser’s centrality on the placement of her students. However, this relies on the assumption that changes in the centrality of the adviser’s coauthors only influence the placement of the adviser’s students by changing the centrality of the adviser. This will not be true if the aforementioned variable is correlated with an unobserved adviser characteristic which also affects placement. Consider for example a helpful adviser’s who could have helpful co-authors who are more likely to have changes to their connectedness because many people want to work with them. As a robustness check against this kind of argument, in table 6, we report regression results repeating the above analysis but using the average centrality rank of the adviser’s *second* (or indirect) neighbors. The idea is that the clustering of unobserved characteristics must die with distance. An adviser’s second neighbors are much less likely to share the adviser’s unobserved characteristic. We show that the placement of the adviser’s students is still significantly affected by the centrality of the adviser’s second neighbors. This also strengthens our argument for the importance of even indirect connections in job placement. Columns 1,2 and 3 include adviser-fixed effects, while columns 4 and 5 are without adviser-fixed effects. Columns 3 and 5 include an interaction term with market tightness and thus exclude year-fixed effects.

Table 4: Results of Ordered logistic regression for rank of initial placement, adviser coauthor centrality sample.

	Placement Rank		
	(1)	(2)	(3)
Adv. neigh. mean	0.0000940^{**}	0.000146^{**}	0.0000748^{***}
Eigenvector rank	$p = 0.040$	$p = 0.012$	$p = 0.001$
Same sex	0.296	0.0368	-0.353^{*}
	$p = 0.532$	$p = 0.952$	$p = 0.093$
Female student	0.560	0.378	−0.230
	$p = 0.312$	$p = 0.544$	$p = 0.375$
PhD School Rank	0.0148^{**}		0.00958^{***}
	$p = 0.027$		$p = 0.000$
Euclidean Index	−0.000478	−0.000425	−0.000842
	$p = 0.415$	$p = 0.511$	$p = 0.155$
Experience	−0.0199	0.0219	0.0127
	$p = 0.823$	$p = 0.875$	$p = 0.742$
Experience^2	0.000364	−0.00129	−0.000121
	$p = 0.822$	$p = 0.655$	$p = 0.881$
Adviser-fixed effects	*Yes*	*Yes*	*No*
PhD School-fixed effects	*No*	*Yes*	*Yes*
Year-fixed effects	*Yes*	*Yes*	*Yes*
Field-fixed effects	*Yes*	*Yes*	*Yes*
Clustered SE	PhD School	PhD School	PhD School
N	277	277	566

Notes: ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. *Placement Rank* is the Tilburg rank of the student's placement in the year of the placement. *Female student* equals 1 if the student's first name is estimated to be a female first name. *Same sex* equals 1 if both the student and the adviser are estimated to be of the same sex. *Adv. neigh. mean Eigenvector rank* is the mean Eigenvector centrality rank of all coauthors of a student's adviser in the weighted coauthor network in the year of the student's placement. *Market tightness* for a field in a given year is the number of students graduating in that year in that field, divided by the number of AEA-reported job openings in that field in that year, where field is measured by JEL code (equation (1)). *PhD School Rank* is the Tilburg Economics rank of the PhD-awarding university in the year the student finished. *Euclidean Index* is the adviser's Euclidean index of citations in the year the student graduated. *Experience* is the number of years between an adviser's first publication and the year in which the student graduated. *Experience^2* is its square. *PhD School Rank* is the Tilburg rank of the student's PhD granting institution in the year of the student's graduation.

Table 5: Results of Ordered Logistic regression for rank of initial placement interacted with market tightness, adviser coauthor centrality sample.

	Placement Rank		
	(1)	(2)	(3)
Adv. neigh. mean Eigenvector rank	−0.00000310	0.00000887	0.0000519
	$p = 0.966$	$p = 0.932$	$p = 0.216$
Market Tightness	−0.236	−2.351	−0.954
	$p = 0.924$	$p = 0.397$	$p = 0.579$
Adv. neigh. mean Eigenvector rank × Market Tightness	0.000288*	0.000382*	0.0000807
	$p = 0.059$	$p = 0.083$	$p = 0.513$
Same sex	0.116	−0.333	−0.403*
	$p = 0.841$	$p = 0.685$	$p = 0.060$
Female student	0.406	0.0732	−0.310
	$p = 0.527$	$p = 0.925$	$p = 0.258$
PhD School Rank	0.0147**		0.00889***
	$p = 0.020$		$p = 0.000$
Euclidean Index	−0.000466	−0.000198	−0.000877
	$p = 0.367$	$p = 0.719$	$p = 0.115$
Experience	−0.0268	0.0276	0.00731
	$p = 0.753$	$p = 0.824$	$p = 0.840$
Experience^2	0.000455	−0.00118	0.0000757
	$p = 0.763$	$p = 0.652$	$p = 0.920$
Adviser-fixed effects	*Yes*	*Yes*	*No*
School-fixed effects	*No*	*Yes*	*Yes*
Year-fixed effects	*No*	*No*	*No*
Field-fixed effects	*Yes*	*Yes*	*Yes*
Clustered SE	PhD School	PhD School	PhD School
N	277	277	566

Notes: ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. *Placement Rank* is the Tilburg rank of the student's placement in the year of the placement. *Adv. neigh. mean Eigenvector rank* is the mean Eigenvector centrality rank of all coauthors of the student's adviser in the weighted coauthor network in the year of the student's placement. *Female student* equals 1 if the student's first name is estimated to be a female first name. *Same sex* equals 1 if both the student and the adviser are estimated to be of the same sex. *Market tightness* for a field in a given year is the number of students graduating in that year in that field, divided by the number of AEA-reported job openings in that field in that year, where field is measured by JEL code (equation (1)).*Euclidean Index* is the adviser's Euclidean index of citations in the year the student graduated. *Experience* is the number of years between an adviser's first publication and the year in which the student graduated. *Experience*^{2} is its square. *PhD School Rank* is the Tilburg rank of the student's PhD granting institution in the year of the student's graduation.

Table 6: Results of Ordered logistic regression for rank of initial placement for second neighbor centrality ranks, adviser coauthor centrality sample.

	Placement Rank				
	(1)	(2)	(3)	(4)	(5)
Adv. 2ndneigh. mean Eigenvector rank	0.000117*	0.000159**	−0.0000451	0.0000782***	0.0000415
	$p = 0.062$	$p = 0.014$	$p = 0.637$	$p = 0.007$	$p = 0.390$
Female student	0.682	0.615	0.600	−0.159	−0.241
	$p = 0.200$	$p = 0.348$	$p = 0.285$	$p = 0.547$	$p = 0.391$
Same sex	0.391	0.263	0.257	−0.284	−0.338
	$p = 0.392$	$p = 0.677$	$p = 0.608$	$p = 0.184$	$p = 0.126$
PhD School Rank	0.0144**		0.0145**	0.00949***	0.00879***
	$p = 0.028$		$p = 0.017$	$p = 0.000$	$p = 0.000$
Euclidean Index	−0.000476	−0.000418	−0.000504	−0.000882	−0.000918
	$p = 0.441$	$p = 0.514$	$p = 0.330$	$p = 0.143$	$p = 0.104$
Experience	−0.0155	0.0161	−0.0216	0.0141	0.00924
	$p = 0.856$	$p = 0.903$	$p = 0.790$	$p = 0.707$	$p = 0.791$
Experience^2	0.000370	−0.00110	0.000440	−0.0000990	0.0000857
	$p = 0.813$	$p = 0.688$	$p = 0.763$	$p = 0.898$	$p = 0.903$
Market Tightness			−1.382		−1.390
			$p = 0.613$		$p = 0.443$
Adv. 2ndneigh. mean w Eigenvector rank × Market Tightness			0.000466*		0.000123
			$p = 0.058$		$p = 0.414$
Adviser-fixed effects	*Yes*	*Yes*	*Yes*	*No*	*No*
PhD School-fixed effects	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Field-fixed effects	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Year-fixed effects	*Yes*	*Yes*	*No*	*Yes*	*No*
Clustered SE	PhD School	PhD School	PhD School	PhD School	PhD School
N	277	277	277	566	566

Notes: ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. *Placement Rank* is the Tilburg rank of the student's placement in the year of the placement. *Adv. 2nd neigh. mean Eigenvector rank* is the mean Eigenvector centrality rank of all indirect coauthors of the student's adviser in the weighted coauthor network in the year of the student's placement. *Female student* equals 1 if the student's first name is estimated to be a female first name. *Same sex* equals 1 if both the student and the adviser are estimated to be of the same sex. *PhD School Rank* is the Tilburg rank of the student's PhD granting institution in the year of the student's graduation. *Market tightness* for a field in a given year is the number of students graduating in that year in that field, divided by the number of AEA-reported job openings in that field in that year, where field is measured by JEL code (equation (1)). *Euclidean Index* is the adviser's Euclidean index of citations in the year the student graduated. *Experience* is the number of years between an adviser's first publication and the year in which the student graduated. *Experience*^{2} is its square.

5.2 Social Distance and Placement probability

In this subsection, we present additional evidence that an adviser's connections in the academic network matter for her student's placement. We show that the social distance between an adviser and a department affects the probability of the adviser placing her student at that department.

Hitherto, we have focused on identifying the impact of adviser centrality on the rank of her student's placement. In the data sample for this subsection, which we term "adviser distance sample", the unit of observation is the connection between advisers and placement university's faculty members. We look at all possible paths between every adviser and every possible university that satisfies three conditions: a) there is a Tilburg Economics Department rank available for the university, b) we know the faculty members from the Hasselback rosters add and c) at least one faculty member is in the co-author network. We then count the number of steps one has to take to go from an adviser a to the closest member of university k (where each step is a co-author link). Thus, we define the distance between an adviser a and a university k by the length of the shortest path. In order to identify the impact of this 'social distance' between an adviser and a prospective placement university on the placement of the adviser's student, we construct a variable that measures the increase in social distance caused by the death of authors somewhere in the network. The dependent variable is whether one of a's students were placed at university k in t.

We estimate the following regression equation in a logistic regression model[28]:

$$\begin{aligned} Placement_{akt} =& \beta_0 + \beta_1 \text{IncreaseInSocialDistanceAfterDeath}_{akt} + \beta_2 \text{SocialDistanceBeforeDeath}_{akt} + \\ & \gamma_1 \text{PlacementRank}_{kt} + a + \text{PhDSchool}_j + t + \epsilon_{jkt} \end{aligned} \tag{4}$$

We are interested in coefficients β_1 and β_2. Since the social distance increases due to the removal of deceased authors, we expect β_1 to be negative, as this indicates a lower probability of student placement at k. The variable $\textit{SocialDistanceBeforeDeath}_{akt}$ indicates the length of the shortest path between adviser a to the nearest faculty member of k in the co-author network in year t, given that the path exists (before accounting for the change in distance due to death of authors). We expect this coefficient to be negative (though not identified) since a shorter distance to another faculty should result in a higher placement probability if social connections do play a role in placement. $\textit{PlacementRank}_{kt}$ is the Tilburg

[28] Results of a probit model are qualitatively the same.

Economics Department rank of university k in year t. Fixed effects for adviser a and the student's Phd granting school $PhDSchool_j$ capture unobserved characteristics, while fixed effects for year of placement capture market characteristics for that year. In a variant of the model we remove adviser-fixed effects to gain more observations, and instead we control for adviser characteristics such as her Euclidean Index of citations, her experience and the squared experience. In all variants of the model we cluster standard errors around *PhDSchool* to account for unobserved heterogeneity and different group sizes.

Table 7: Summary statistics for adviser distance sample.

	N	Mean	Median	Std.Dev.	Min	Max
Student placement	1264					
Increase in social dist. after death	46485	1.50	1	0.86	1	11
Social dist. before death	959770	8.72	8	2.74	2	32
Placement Rank	1394345	161.33	80	272.06	0	2554
Euclidean Index	1394345	19.27	19	9.09	0	62
Experience	1404616	297.34	268	223.60	1	845
Male adv.	1404616	0.91	1	0.28	0	1

Notes: All variables refer to time-variant dyads between adviser a and placement k in year t, given that k appears in the Tilburg Economics Ranking and a list of faculty members is available. *Student Placement* equals 1 if a student of adviser a was placed at university k in year t. *Increase in social dist. after death* is the increase in social distance in the co-author network between a and the nearest faculty member of k after scientist died in year $t-1$. *Social dist. before death* is the social distance in the co-author network between a and the nearest faculty member of k before the distance changed induced by the removal of deceased scientists. *Placement Rank* is the Tilburg Economics rank of university k in year t. *Euclidean Index* is the adviser's Euclidean index of citations in year t. *Experience* is the number of years between an adviser's first publication and year t. *Male adv.* equals 1 if the adviser is estimated to not be female. Only paths between known advisers of students graduating from North-American universities and identified faculty members of departments with Tilburg Economics Department rank and listing in the Hasselback faculty roosters considered.

Table 7 presents summary statistics for the adviser distance sample. The total number of dyads (adviser-university pairs) is $2,706,900$, of which $1,404,616$ include existing paths between adviser a and the closest faculty member of k in year t. For $46,485$ of these, the social distance increased due to the exogenous shock of author deaths, sometimes up to 11 steps. Corresponding correlation coefficients are given in table 12 (in the appendix).

Table 8 presents results of a logistic regression for model 4 with standard errors clustered around PhD School. As expected, the coefficient of social distance in the co-author network before death is negative, indicating that students are more likely to be placed at faculties to which their adviser has a shorter distance. A one unit increase in the distance to university k decreases the odds of being placed at

k by $e^{-0.349} - 1 \approx 29\%$ (at the mean co-author distance before death (1.5) and holding all other variables fixed at the mean). The coefficients change marginally in column (2), where we control for the PhD School rather than the adviser. The p values for both models fluctuate around a value of 0.1, indicating weak statistical significance.

Table 8: Results of a logistic regression for placement probability in adviser distance sample.

	Student placement	
	(1)	(2)
Increase in social dist. after death	-0.349^{*}	-0.347
	$p = 0.095$	$p = 0.120$
Social dist. before death	-0.218^{***}	-0.189^{***}
	$p = 0.000$	$p = 0.000$
Placement Rank	-0.00524^{***}	-0.00546^{***}
	$p = 0.000$	$p = 0.000$
Euclidean Index	0.000690^{***}	0.000594^{***}
	$p = 0.001$	$p = 0.000$
Experience	0.0191	0.0345
	$p = 0.518$	$p = 0.248$
Experience^2	-0.000679	-0.00105
	$p = 0.306$	$p = 0.153$
Female adviser		-0.732^{***}
		$p = 0.003$
Constant	-4.450^{***}	-4.983^{***}
	$p = 0.000$	$p = 0.000$
Adviser-FE	Yes	No
PhD School-FE	No	Yes
Placement year-FE	Yes	Yes
Clustered SE	PhD School	PhD School
N	889,474	869,736

Notes: ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. All variables refer to time-variant dyads between adviser a and placement k in year t, given that k appears in the Tilburg Economics Ranking and a list of faculty members is available. *Student Placement* equals 1 if a student of adviser a was placed at university k in year t. *Increase in social dist. after death* is the increase in social distance in the co-author network between a and the nearest faculty member of k after scientist died in year $t-1$. *Social dist. before death* is the social distance in the co-author network between a and the nearest faculty member of k before the exogenous removal of deceased authors. *Placement Rank* is the Tilburg Economics rank of university k in year t. *Euclidean Index* is the adviser's Euclidean index of citations in year t. *Experience* is the number of years between an adviser's first publication and year t. *Experience^2* is its square. *Male adv.* equals 1 if the adviser is estimated to not be female. Only paths between known advisers of students graduating from North-American universities and identified faculty members of departments with Tilburg Economics Department rank and listing in the Hasselback faculty roosters considered.

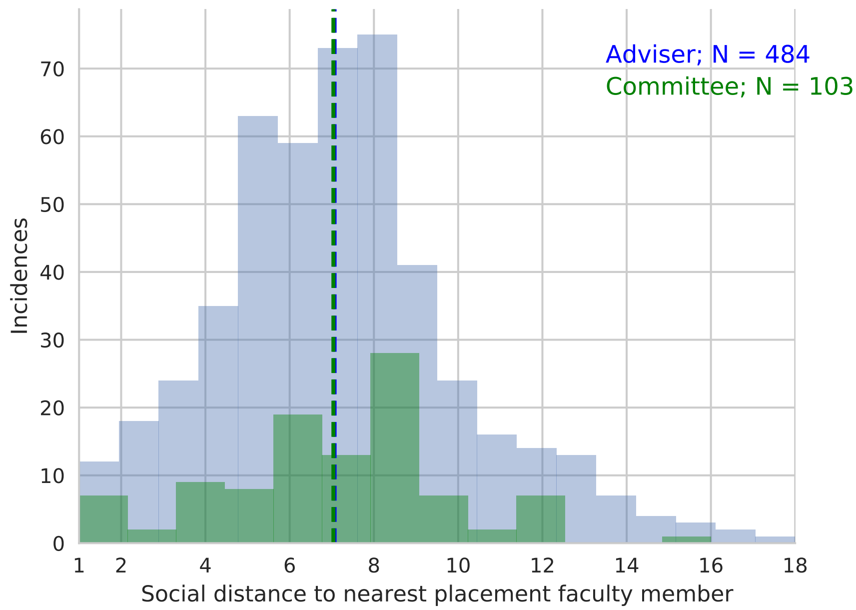
5.3 Channel

We want to argue that an adviser's connectedness in the co-author network matters for her student's placement because it reduces information asymmetry regarding the match quality of a student with a university. Other theoretically possible channels include reciprocity and favoritism. We will provide supporting empirical analysis (without showing any causality) to argue that the latter channels are not very important.

Reciprocity refers to a direct exchange of students in the same or subsequent years between two universities ('*I hire your students, you hire mine*'). More connected advisers may have more of these reciprocal relationships which would affect student placement. To assess the importance of this channel we construct a network of PhD granting schools connected via directed links whenever one school places a PhD student in the other. There are 319 non-zero links between universities of which only 4% of all ties are bi-directional i.e. both universities hired a student from the other (indicating an exchange of students). Being very rare, bidirectional links tend to occur more often with top schools, i.a. a student moving from Harvard to MIT and vice versa. Based on the low number, we rule out reciprocity as an important channel through which adviser connectedness affects student placement.

We defined favoritism vis-a-vis the student's adviser as hiring of her student by her coauthors' university, i.e. the student is placed in the adviser's coauthors' department. Bian et al. (2016) study the extent of favoritism with senior hiring in the German academic market. They define favoritism as hirings of senior researchers that were colleagues with individuals working in the hiring department. We assess the importance of this channel by an estimation of the minimum social distance between an adviser and faculty members of the university where her student got placed. Social distance is defined as number of intermediate nodes between any two nodes in the network, given that a path exists between them. For example, if the student is placed in the adviser's coauthors' department, the corresponding social distance would be 1. On the other hand if a student is placed at a department where her adviser has no co-authors but one of her adviser's co-authors has a co-author, the social distance is 2. Figure 1 indicates that out of the 484 advisers for whom we can connect adviser and student's placement faculty members (through some path of co-authors), only 13 times did the student go to an adviser's coauthor's university. This further strengthens our assertion that indirect connections matter a lot for job placement (over and above direct connections). In a further 15 cases, the minimum social distance between the adviser and the nearest placement faculty member is 2. The mean social distance between an adviser and her student's placement is 7. That is, on average there are 6 researchers between the adviser and her student's placement faculty. Given the high average social distance between the adviser and the student's placement, we conclude that there is little favoritism in the Economics job market.[29]

Figure 1: Histogram of minimum social distance to placement faculty.



Notes: Histogram shows social distance between a student's adviser and the nearest member of the placement faculty. Social distance is the number of nodes on a path between nodes and is measured in the coauthor network of the year of placement.

It could be argued that adviser connectedness helps student placement if some departments are afraid of refusing students of advisers who are influential in their field. However, we believe that by including controls for the adviser's productivity, age, gender and affiliation, we are able to control for this effect.

6 Discussion and Conclusion

We show that students receive better placement outcomes when their adviser is better connected in the Economics co-author network. We provide supportive evidence to argue that this could be because more central advisers are better positioned to disseminate information in the network, which ultimately de-

[29] The finding of a relatively high social distance is also interesting in light of the findings of Baruffaldi et al. (2016). The authors relate a PhD student's productivity to where she obtained the previous academic degree. They find PhD students trained at the affiliations of the new supervisor's coauthors are most productive, i.e. where the social distance is non-zero, but small.

creases information asymmetry regarding the match quality of her student with a prospective university. Our research is relevant for understanding the placement of graduate students. Since initial placement matters a lot for an Economist's career (Oyer, 2006), the effort dedicated to understanding it, can hardly be overstated.

Furthermore, our result that the connectedness of the adviser matters for the placement of Economics graduates has insights into possible results in the general labor market. Hitherto, several papers have documented that referrals and job opening information from currently employed workers matters for job seeking individuals. However, we demonstrate that not all connections are equal - more connected workers[30] could be more important for job seekers. We also demonstrate through our study that indirect connections could be an important determinant of job market outcome. Finally, due to the special characteristics of the Economics Job Market, one of which is that there is no information asymmetry regarding job openings, we are able to provide some evidence to argue that social networks serve as a conduit of information regarding an applicant's quality.

Further avenues for research include the quality of a job match. Ultimately, the Economics job market is not necessarily about matching the student with the highest ranked department, but to improve the match between the student and the department (Smeets et al., 2006). It would be interesting to see how students matched after recommendations/calls from the adviser fare in the academic world. A good measure of match quality would be if the student gets tenure at the university which first hires the student. Another extension of our work would be to study how adviser connections in industry could affect non-academic placements.

[30]This could be in the network of all jobs held (where two workers are connected if they have ever worked in the same firm at the same time), or in the networks of colleagues, friends and acquaintances.

A Appendix

A.1 Variables description

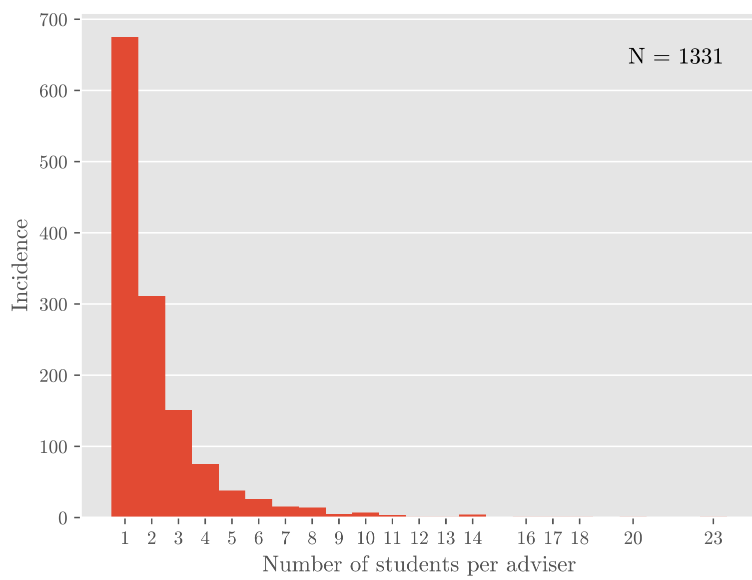
Throughout this paper we use two samples: The "adviser coauthor centrality sample" and the "adviser distance sample", whose variables are explained in greater detail below.

The "adviser coauthor centrality sample" is used to identify the effect of the centrality of an adviser on her student's placement outcome. The dependent variable is Placement Rank, the rank of the student's initial placement according to the Tilburg University Economics ranking in year t. Our variable of interest is Adv. neigh. mean Eigenvector rank and is computed as follows: First we define the co-author network based on all publications in a set of 408 journals, where two researchers are connected whenever they publish a paper. The link weight (or strength) corresponds to the number of jointly published papers. For a student placement in year t we include all publications between the year 1997 and year $t+1$. Second, we compute for every node in the network the rank according to her Eigenvector centrality computed according to equation (2). Then we average all Eigenvector centrality ranks over all coauthors of an adviser present in the network. Control variables for an author include Euclidean Index, Experience, Experience^2, and Same sex. Euclidean Index is the Euclidean index representing the stock of citations in t to all publications published until including t. Experience is the number of years between the adviser's first publication and t, while Experience^2 is the square. These variables are computed using data from Scopus. Same sex equals 1 if both the adviser and the student are estimated to be of same sex as defined by genderize.io database. Student controls include Market tightness, Female student, PhD School Rank, PhD School, Year and Field. Market tightness is a measure of tightness of the Economics job market in t defined as the number of students graduating in the student's field f in the same academic year divided by the number of openings in a student's field, where field is defined by the JEL code (equation (1)). Female student 1 if the student's first name is estimated to be female with probability ≥ 0.5 in the genderize.io database, and 0 otherwise. PhD School Rank is the rank of the student's PhD graduate school according to the Tilburg University Economics ranking in the year she obtained her PhD. Year is a dummy variables for the year the student was placed. PhD School is a dummy variable for the student's university and Field is a dummy variable for the student's field. The last two variables are taken from the annually published lists on dissertations in Economics at North American universities.

The "adviser distance sample" serves to identify the effect of an increase in the social distance between an adviser and a university on the probability that one of her students is placed at that university. The unit of observation is the dyad between adviser a and university k in year t. We define a university as any university for which we know its faculty members from the Hasselback faculty rosters. We count the number of co-authors between adviser a and every faculty member at k and take the minimum of that. Our variable thus computes the shortest social distance between a and k. The dependent variable is a binary variable indicating whether one of a's was initially placed at k in t. The variable of interest is Increase in social dist. after death and indicates the increase in the social distance between a and k due to the death of a scholar somewhere in the network. Social dist. before death is the social distance between j and k as observed from co-authored publications in Economics journals published between 1997 and t. Placement rank is the Tilburg University Economics rank of k in t.

A.2 Additional tables and figures

Figure 2: Histogram showing the number of students per adviser (academic years 2000/01-2003/04).



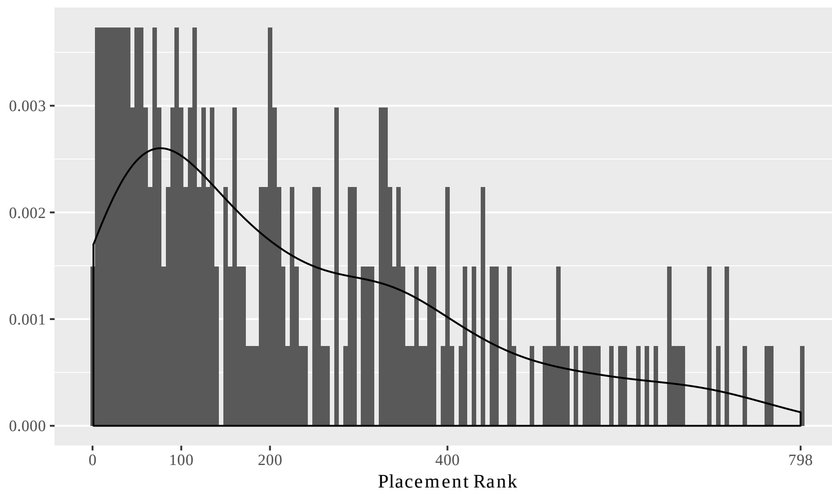
Notes: Histogram shows the number of advisers (y axis) with a given number of students (x axis). Only students with known adviser from North-American universities that graduated in the academic years 2000/2001, 2001/2002, and 2002/2003 considered.

Table 9: Advisers with most PhD students, 2000-2003.

	Name	Students	University	Citations	Euclid	Seniority
1	Daron Acemoglu	23	Massachusetts Institute of Technology	1633.0	154.91	10
2	Andrei Shleifer	20	Harvard University	18221.0	1038.39	17
3	Roger R. Betancourt	18	University of Maryland	481.0	31.45	32
4	John Y. Campbell	17	Harvard University	9491.0	497.63	17
5	Peter C.B. Phillips	16	Yale University	24258.0	1684.27	30
6	Arnold C. Harberger	14	University of California, Los Angeles	426.0	36.59	47
6	Lawrence F. Katz	14	Harvard University	6369.0	606.60	22
6	Olivier Jean Blanchard	14	Massachusetts Institute of Technology	8069.0	587.32	24
6	Ronald Andrew Ratti	14	University of Missouri	182.0	25.28	26
10	Abhijit V. Banerjee	13	Massachusetts Institute of Technology	2432.0	323.58	12
11	Ricardo J. Caballero	12	Massachusetts Institute of Technology	2022.0	158.80	14
12	Dominick Salvatore	11	Fordham University	801.0	42.50	31
12	George W. Evans	11	University of Oregon	1471.0	87.53	19
12	John C. Haltiwanger	11	University of Maryland	2276.0	219.18	21
15	James M. Poterba	10	Massachusetts Institute of Technology	6484.0	485.51	20
15	Joshua D. Angrist	10	Massachusetts Institute of Technology	2047.0	241.62	13
15	Larry A. Sjaastad	10	Texas A&M University and University of Chicago	243.0	23.15	43
15	Robert A. Moffitt	10	Johns Hopkins University	2718.0	140.84	26
15	Stephen J. Turnovsky	10	University of Washington	5537.0	152.15	35
15	Thomas D. Willett	10	Claremont Graduate University	2202.0	87.54	35
15	Thomas J. Holmes	10	University of Minnesota	112.0	22.38	11

Notes: Table lists PhD advisers by number of PhD students that graduated at North American Economics departments in the academic years 2000/2001, 2001/2002, 2002/2003. *Students* is the number of students that graduated with this adviser and that have a Scopus profile. *Citations* is the number of citations to that author. *Publications* is the number of publications of that author. *Seniority* is the number of years since the first publication. All information originate from Scopus and were obtained in March 2017. Only advisers with Scopus profile considered. Co-advised students count as full supervised students.

Figure 3: Distribution of placement rank of initial placement.



Notes: Graph shows the distribution of the initial placement of students in our dataset. Only students with known adviser from North-American universities that graduated in the academic years 2000/2001, 2001/2002, and 2002/2003 considered, whose initial placement is ranked in the Tilburg Economics Department ranking.

Table 10: Summary statistics for all continuous variables in the adviser coauthor centrality sample.

Placement Rank		0.18	−0.01	0.48	−0.37	0.02
Adv. neigh. mean Eigenvector rank	0.21		0.12	0.13	−0.04	0.11
Market tightness	0.04	0.11		−0.10	0.07	0.02
School Rank	0.34	0.12	−0.04		−0.55	0.09
Adv. Euclidean Index	−0.18	−0.10	−0.10	−0.20		0.34
Adv. experience	−0.03	0.11	−0.02	0.15	0.22	

Notes: Upper triangular depicts Spearman correlation coefficients while lower correlation reports Pearson correlation coefficients. *Placement Rank* is the Tilburg Economics rank of a student's placement in the year of the placement. *Adv. neigh. mean Eigenvector rank* is the mean Eigenvector centrality rank of all coauthors of an adviser in the weighted coauthor network corresponding to the year of the placement. *Market tightness* is the field-specific number of students who graduated in a year divided by the in this field number of AEA-reported job openings for that year (equation (1)). *School Rank* is the Tilburg Economics rank of the PhD-awarding university in the year the student finished. *Euclidean Index* is the adviser's Euclidean index of citations in the year the student graduated. *Experience* is the number of years between an adviser's first publication and the year in which the student graduated. *Experience^2* is its square. Only students considered that were placed at an Tilburg-ranked institution, whose adviser is in the network's giant component, and whose adviser has students in different years for which above two conditions hold.

Table 11: List of deceased faculty members in the dataset.

Name	Date of death	Name	Date of death
Dalton, George	1999, Aug 23	Vilasuso, Jon R.	2002, Apr 27
Liu, Jung-Chao	1999, Aug 31	Bowman, Mary Jean	2002, Jun 04
Griliches, Zvi	1999, Nov 04	Smith, Bruce D.	2002, Jul 09
Gapinski, James H.	2000, Jan 01	Ansoff, H. Igor	2002, Jul 14
Johnson, Byron L.	2000, Jan 06	Dornbusch, Rüdiger	2002, Jul 25
Heyne, Paul	2000, Mar 09	Ando, Albert	2002, Sep 19
Miller, Merton H.	2000, Jun 03	Gabriel, Stuart A.	2002, Oct 15
Lillard, Lee A.	2000, Dec 02	Sertel, Murat R.	2003, Jan 25
Elliott, John E.	2001, Jan 01	Johnson, D. Gale	2003, Apr 13
Cameron, Rondo	2001, Jan 01	Berger, Mark C.	2003, Apr 30
Cookingham, Mary E.	2001, Mar 12	Kain, John F.	2003, Aug 03
Rosen, Sherwin	2001, Mar 17	Modigliani, Franco	2003, Sep 25
Moses, Ronald	2001, Jun 20	Lee, Winson	2004, Mar 01
Straub, LaVonne	2002, Jan 24	Laffont, Jean Jacques	2004, May 01
Rosenthal, Robert W.	2002, Feb 07		

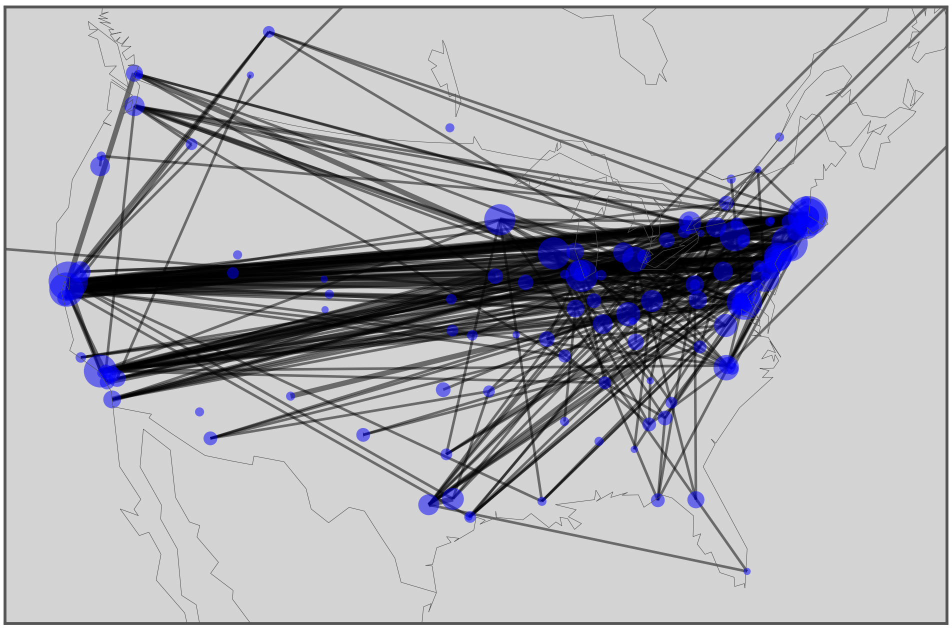
Notes: Table lists 29 authors who passed away between summer 1999 and summer 2004 while serving on the faculty of universities as listed in the Hasselback lists.

Table 12: Correlations for placement probability in the adviser distance sample.

Student placement		1.00	0.00	0.01	0.00	−0.01
Increase in social dist. after death	0.00		−0.03	0.00	1.00	−0.03
Social dist. before death	−0.03	−0.03		−0.03	−0.01	−0.03
Placement Rank	0.01	0.01	−0.14		0.02	−0.01
Euclidean Index	0.00	−0.01	−0.05	0.23		1.00
Experience	−0.03	−0.02	0.40	0.01	0.01	

Notes: Upper triangular depicts Spearman correlation coefficients while lower correlation reports Pearson correlation coefficients. All variables refer to time-variant dyads between adviser a and placement k in year t, given that k appears in the Tilburg Economics Ranking and a list of faculty members is available. *Student Placement* equals 1 if a student of adviser a was placed at university k in year t. *Increase in social dist. after death* is the increase in social distance in the co-author network between a and the nearest faculty member of k after scientist died in year $t-1$. *Social dist. before death* is the social distance in the co-author network between a and the nearest faculty member of k before the distance changed induced by the removal of deceased scientists. *Placement Rank* is the Tilburg Economics rank of university k in year t. *Euclidean Index* is the adviser's Euclidean index of citations in year t. *Experience* is the number of years between an adviser's first publication and year t. *Male adv.* equals 1 if the adviser is estimated to not be female. Only paths between known advisers of students graduating from North-American universities and identified faculty members of departments with Tilburg Economics Department rank and listing in the Hasselback faculty roosters considered.

Figure 4: Hiring network of North American universities 2000/2001-2003/2004.



Notes: Map shows hiring network for North American universities for the academic years 2000-2001, 2001-2002, and 2002-2003. Every node represents a university from which at least one student graduated that was subsequently hired by another university on the map, which is indicated by the links (Nodes representing Hawaiian universities are omitted). Nodes are sized according to how many students graduated from that university. Network is calculated from the placement of 451 students going from/to 132 universities.

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