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Indirect Contacts in Hiring: The Economics Job Market*

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Using two identification strategies, we demonstrate a positive relationship between the connectedness of a PhD adviser (in the coauthor network) and the placement of her student. In method one, identification is achieved by using *changes* in the centrality of the adviser's coauthors in the year of student placement as an exogenous shock to the adviser's centrality. Our second strategy uses the death of faculty members as an exogenous shock to show that the probability of a student being placed at a particular university reduces when the 'social distance' between her adviser and that university increases due to the death.

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

JEL Classification: A11, D83, J44, J64

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1 Introduction

A big labor market for academic Economists is organized annually by the American Economic Association with graduate students, their advisers and hiring institutions as market participants (Coles et al., 2010). The quality of a student's application (job market paper, other research, teaching ability, graduating university etc.) is the most important determinant of success in this labor market. However, hiring institutions do not perfectly observe candidate quality. One reason for this is that due to the sheer number of applications, it is impossible for the hiring committee to look through all applications very carefully.[1] The uncertainty about candidate quality may lead to hiring institutes rejecting candidates who they would have accepted otherwise. It could also lead to some good students being placed at mid level institutions and mid level students being placed at low ranked institutions (we assume that, on average, uncertainty worsens the outcome as better ranked hiring institutes can afford to have a lower tolerance for uncertainty). Reference letters and phone calls from the adviser(s) can assuage this problem (Athey et al., 2016; Colander, 1997).[2] Since an adviser can put in a good word for her student in her academic network, we expect that the 'connectedness' of an adviser should impact the placement of her student in a positive way.[3] So, our research goal is to demonstrate a positive relationship between the connectedness of a student's adviser in the coauthor network and the quality of the student's placement.

We use two identification strategies (with two different placement outcome variables) to show that adviser connectedness affects her student's placement. First, we show that the connectedness of an adviser positively affects the quality of her student's placement university. We define adviser connectedness as the Eigenvector centrality score of the adviser in the network of coauthors in Economics. This notion of connectedness captures not just direct connections to immediate coauthors but also the impact of indirect links - coauthors of coauthors and so on.[4] Indirect links of the adviser could be important for

[1] Several companies in the general labor market also face this problem.

[2] 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". In the general labor market literature, in addition to empirical evidence, there are also 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).

[3] Baruffaldi et al. (2016) provides another example of using social networks to reduce uncertainty about student quality. They show that PhD students who obtained their Master's degree at an affiliation of their adviser's coauthor are more productive than PhD students coming from a university to which their adviser has no links.

[4] If an adviser's coauthor becomes more connected then this adds to the Eigenvector centrality of the adviser also. 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) 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 Eigenvector centrality, and Banerjee et al.

student placement. For example, an adviser may be able to influence the placement of her students by asking her coauthors to put in a good word for them. The quality of a student's placement university is measured by our version of the Tilburg scoring of universities. Our result indicates that a one standard deviation change in the centrality of the adviser causes, on average, the score of the placement institute to improve by 0.95–1.02 standard deviations. The average change in adviser centrality (year on year) is not so high though, and is close to 0.02 (about 0.013 standard deviations). This corresponds to a rank improvement in the placement of her student by about 6 ranks. Section 4 presents more details.

Obviously, there is an endogeneity issue arising from the fact that a more connected adviser is likely to be better 'quality' as well. We identify the impact of adviser connectedness by using the *changes* in the connectedness of the adviser's coauthors in the year of student placement as an exogenous shock to adviser connectedness. The identifying condition here rests on the following ideas. One, *changes* in the connectedness of the adviser's coauthors *in the year of a student's placement* is difficult to anticipate (and therefore use strategically) for both the student and the adviser. This alleviates endogeneity problems like those arising from the possibility of better students choosing to work under more connected advisers. At the time at which a student chooses her adviser, she may know the *level* of her adviser's centrality but it would be very difficult for her to guess the *change* in the centrality of her adviser's coauthors in the year in which she will eventually graduate. Thus, the change in the connectedness of an adviser's coauthors in the year of a student's placement can be thought of as an exogenous shock which changes adviser connectedness in the year of placement, and affects student placement only via this channel. Further, we control for time-invariant unobserved adviser characteristics like 'helpfulness' via adviser-fixed effects. Thus, unobserved adviser quality will not bias our results. We present a deeper discussion of the critical empirical challenges and this identification strategy in section 3.

We demonstrate a link between adviser connectedness and student placement in another way as well. We show that advisers are more likely to place their students at institutions which are 'closer' to them. We define the 'social distance' between an adviser and a hiring institution as the length of the shortest path between the adviser and the institute in the coauthor network. Then, we use the death of economists as an exogenous shock which may affect the social distance. The idea is that a death may break the shortest path between an adviser and an institution. If this happens then the aforementioned social distance increases since the second shortest path is weakly longer than the shortest path. We show

(2013) show that the Eigenvector centrality of the first-informed individual predicts how fast information spreads in a social network.

that an increase in social distance negatively affects the probability of the adviser placing her student at that department. In particular, we find that if the social distance between an adviser and a university increases by one standard deviation (sd), the odds of that adviser's student being placed at that university reduce by about 16.5%. Note that the social distance rarely increases by 1sd. The mean of the increase in social distance is about 0.04sd, and this corresponds to a decrease in probability of being placed by around 4%. We present this analysis in section 5.2.

The contribution of this paper can be separated into two 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 student's recommendation letter writer and the student's placement. We show that even after controlling for 'prominence' (which we equate with the Euclidean index[5] of citations), the connectedness of the adviser matters for her students' placement.

Secondly, though our results are for a unique job market, our results offer two relevant insights for the general labor market as well. One, owing to our special 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 coauthor at a given university, she may still be able to put in a good word for her student there if her coauthor has a coauthor in that university. This distinguishes our paper from those in the literature on referrals who only look at direct links like (Kramarz and Skans, 2014; Burks et al., 2017) where they consider the channel of current employees referring a worker in their current workplace. These papers do a great job of establishing the value of direct connections. However, they do not speak about which workers are more 'connected' than others, and whether connections to these workers matter more 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. 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. Note that we realize that the general labor market does not have an 'adviser' who places workers. However, at its heart,

[5] The Euclidean index of citations is the Euclidean sum of publications represented by their citation stock for any given year, as proposed by Perry and Reny (2016).

this paper is about pointing out that links with more connected people are more valuable in a job search than. This message will be true for any labor market with information frictions.

Furthermore, in general, the literature on job search (Granovetter, 1973; Bayer et al., 2008) is unable to distinguish between two channels via which social networks usually affect labor market outcomes: learning about new job openings versus reducing uncertainty about the job candidate. By focusing on the Economics job market where there is very little lack of information about new job openings (thanks to Job Openings for Economists), we provide 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.[6]

The rest of the paper is organized as follows. In section 2, we summarize the relevant literature and highlight our contribution. Section 3 presents a deeper discussion of our empirical strategies. The data construction and description is in section 4, and our empirical analysis is described in section 5. Section 6 concludes our paper.

2 Literature

Our paper is closely related to the literature on referrals in the job market, and more generally the job search literature. It is also related to the relatively smaller set of papers which talk about the academic job market. We will discuss the relevant papers in each of these literatures and highlight our contribution.

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) show that job search networks help reduce information deficiencies in the market and consequently referral-based job searches lead to better matches. Burks et al. (2017) 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 does a great job of making clear that knowing a cur-

[6]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 the channel side is that of a reduction in information asymmetry - this could be regarding student quality or about other variables which can affect the match quality.

rently employed worker at a firm can increase the probability of landing a job at that firm for a job seeker. However, these papers 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? One reason this question has not been addressed is the lack of an appropriately rich data set. Our paper contributes to the literature on job search by using a unique data set to map the network of connections (coauthor network) to show a causal relationship between the connectedness of a person and job market outcomes of job seekers who have a link with that person. 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 and children and establish that this connection is important for the job market outcome of the children. Burks et al. (2017) and 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 do not capture how the worker can use this information to help a job seeker get a 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 socio-economic characteristics. 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. In contrast, our data allows us to precisely link economists whenever they have published a research article.

The literature on job search teaches us that 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 worker and the employer about the worker's ability (Montgomery, 1991; Burks et al., 2017; Dustmann et al., 2016).[7] However, studies which look at the former channel - like those which study the impact of neighborhoods and other 'local' networks on job search, often find it difficult to 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 Economics job market where job seekers have almost full information about all the new job openings. This is because most job openings are posted in Job Openings for Economists (JOE). Thus, the setting in our paper is particularly conducive to studying how much

[7] Nepotism and reciprocity are also possible channels. We talk a little bit about these in section 5.3.

social connections can help by reducing information asymmetry about the quality of the job candidate. A related paper is that of Baruffaldi et al. (2016) who 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 that PhD students hired from masters programs at affiliations from which the adviser of the PhD student draws coauthors have, on average, a higher productivity compared to students hired from universities to which their adviser has no links.

The literature on the Economics job market is relatively small. Our paper is the first to study the relationship between the connectedness of the PhD adviser and the placement of her student(s). Previous studies have shown the value of different variables on student placement. 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' (as determined by the authors subjectively) of the student's recommendation letter writer helps the student's placement. Smeets et al. (2006) show that the academic job 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.

3 Empirical Issues and Identification Strategy

Our objective is to identify a causal relationship between adviser connectedness and student placement. However, an adviser's connectedness in the network of coauthors is not exogenous: advisers who are more productive, more experienced or affiliated with better universities 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 (and we do control for these), there may 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.

We use the above idea in two ways. One, we identify the impact of adviser connectedness on student placement by utilizing the *changes* in the connectedness of the adviser's coauthors as an exogenous shock to the adviser's centrality in the year of student placement. The connectedness of an adviser's coauthors' can change when her coauthors publish new papers (with old or new coauthors). This affects the centrality score of the adviser as well. To avoid having changes in the adviser's own centrality causing the change in her coauthors' centrality, we compute the centralities of the adviser's coauthors' in the coauthor network which excludes the adviser herself. While the centrality *level* of an adviser's coauthors is endogenously determined, our identifying assumption is that the *change* in the connectedness of an adviser's coauthors *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, 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 account for unobserved time-invariant adviser characteristics. Adviser fixed effects requires us to use only those advisers who place graduate students in more than one year in our data set.[8] Hence, for analysis using this identification strategy, we exclude students whose advisers did not place another student in another year in our sample. We estimate a two-stage least squares (2SLS) regression where the main explanatory variable is the adviser's Eigenvector centrality score, and the mean Eigenvector centrality score of the adviser's coauthors acts as the instrument.

The second way through which we establish a positive relationship between adviser connectedness and her student's placement is as follows. Suppose the distance between a university and an adviser is defined as the length of the shortest path in the coauthor network between the adviser and any faculty member at the university. We use the death of economists anywhere in the coauthor network as an exogenous shock which affects the social distance between an adviser and different university. Note that the death of an economist can only increase the distance between an adviser and a university by breaking the shortest coauthor path the adviser had to that university. 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 university. 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., 2019).

Next, we discuss more specific channels which could affect our results and how we handle them.

[8] In general adviser fixed effects would also be useful if the adviser places multiple students in any one year. However, adviser centrality will only change across different years, and we are interested in the impact of adviser centrality on student placement.

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 advisers 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 time-invariant 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.

Second, can unobserved student quality and assortative matching 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. This concern is mitigated because 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 coauthors in the year in which the student gets placed.[9] However, we believe that it is hard for students (and advisers) to anticipate the change in connectedness[10] of their adviser's coauthors' *in the year of their placement*. Thus, we argue that the change in the centrality of the adviser's coauthors affects student placement only via (exogenously) changing the adviser's connectedness.

Another channel which could potentially influence our results is that of clustering. The concern with clustering is that advisers and their coauthors share similar qualities. A correlation between the qualities of the adviser and her coauthors may make the reader question our first identification strategy. However, note two things. First, our identification is based on changes in the centrality of the adviser's coauthors, not on the level. It is not clear why changes in the centrality of the adviser's coauthors in the year of a student's placement should influence the student's placement in any way apart from changing

[9] For our second identification strategy, we think that the exogeneity of the death of economists is a reasonable assumption. It is extremely unlikely that the strength of assortative matching is correlated with it.

[10] 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 coauthors in their expected future graduation year.

the centrality of her adviser in that period. Second, we control for time invariant adviser qualities directly via adviser fixed effects and we control for some time varying adviser qualities like publication index, experience, sex explicitly. Furthermore, the impact of clustering must die down with distance from the adviser. That is, the probability of the adviser and her coauthors sharing a quality reduces with distance. As a robustness check, we look at the coauthors of an adviser's coauthors (i.e. the second neighbors of the adviser) and then take their connectedness as our IV for adviser connectedness.

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 (JEL category) 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 under study, 1999-2004.

Due to data limitations and our identifying restrictions, we drop several observations. We must include adviser fixed effects to rule out unobserved (but time invariant) adviser characteristics influencing placements. Adviser fixed effects are relevant for only those students whose adviser placed students in multiple years between 2000-2004. This gives us a sample of 689 observations. Naturally, since our students/observations come from those advisers who have placed students in more than one year between 2000-2004, our sample is not a representative sample of the entire body of graduates. Therefore we caution against interpreting the coefficients as average population effects. We also drop students who were placed in institutions which are not ranked by our measure of institute rankings (this would be because we don't have their publication records), or whose adviser is not in the giant component of the coauthor network.[11] We are left with a sample of 418 observations on which we run our analysis.

[11] The giant component is the largest connected component of the coauthor network. It only makes sense to compare centrality measures of connectedness within the same component.

4 Data

4.1 Doctoral Dissertations in Economics

We focus our analysis on four academic years, namely 2000/2001, 2001/2002, 2002/2003, and 2003/2004. This is in accordance with availability of supplementary data on faculties since the Hasselback list of faculty directories for Economics is not available after 2006. Also, during this period we capture precisely the entire boom period of the early 2000s, but do not interfere with other phases of the business cycle. Most importantly, our study period ends before the beginning of the Great Recession. Therefore all students in our sample face similar non-academic market conditions. The endogeneity of students' market entry choice with changes in the business cycle is discussed in (Gallet et al., 2005).

Lists of new Economics PhDs from faculties in the USA and Canada are published annually in the December issue of the Journal of Economic Literature (JEL). EconLit provides few corrections and additions. We use information from both the JEL lists and EconLit to include the JEL field of the student's dissertation along with the student's year of graduation, and the university which granted the student his/her doctorate. Table 5 gives an account of the number of students by year and field. Finally we estimate the gender of students and advisers based on their first name using the genderize.io database.[12]

We obtain information about the student's advisers from four sources. First, we use the genealogy database of the Research Papers in Economics (RePEc) project.[13] Second, we obtain adviser information from academic departments, either through public sources in the form of websites, or privately through direct emails.[14] Third, we collect CVs of the students themselves. This is the main source of information. The fourth source includes various online sources such as academic tree or Mathematics Genealogy Project. We retrieve publications and citations data for each adviser from Elsevier's Scopus database using Rose and Kitchin (2019) and compute their Euclidean index of citations for each year. This serves as main measure of adviser productivity. Perry and Reny (2016) show that, unlike other indices (such as the h-index), the Euclidean index of citations has desirable properties if one is interested in combining citation stock and publication count.

[12] See genderize.io.

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

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

4.2 Economics Job Market

Information on initial placements is available either through the student's CV or from their former departments directly. Figure 4 shows that the hiring network for the students in our data set is very heterogeneous. To measure the quality of the initial placement we convert the initial placement into placement scores. We use the *method* of the Tilburg Economics University Ranking to score universities according to their research output. The Tilburg Economics University Ranking uses a weighted publication output in 79 predefined journals to assign points to the authors' main affiliation.[15] While the Tilburg ranking uses Web of Science data, we use Scopus, which has both a larger coverage and disambiguated affiliation profiles. We gain 196 students in our data set due to this choice. We use the Scimago Journal Impact Factor, rather than the Web of Science Journal Citation reports, in the year of the publication as journal weight because it was computed using data from Scopus and thus complements our data source.[16] Figure 3 (in the appendix) gives an account of the distribution of the score of the initial placements in the final sample.[17]

4.3 Networks of Collaboration

Our variable of interest is adviser connectedness in the Economics coauthor network. In a coauthor network, jointly published research articles connect any two researchers. Coauthor networks have sparked great interest among Economists. Goyal et al. (2006) for example, have shown that Economics coauthor 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.

We construct coauthor networks from 265,153 articles published in 466 journals between 1937 and 2005. The year 1937 corresponds to the year of first publication of the most senior adviser in our data set. Our analysis covers the period up until 2004, and we include coauthor ties visible one year later as well (since the research project must have begun earlier). The set of journals from which we draw our coauthor network is defined according to the rankings of Combes and Linnemer (2010). We include every journal ranked C or higher in any field wise ranking or in the ranking of the general category. Scopus has

[15] See https://econtop.uvt.nl/methodology.php.

[16] Spearman correlation between our version and the original one for 2004 equals 0.91.

[17] Estimations using the unweighted count of publications in these 79 journals do not alter the qualitative results. The likely reason is that the 79 Economics journals used to measure the weighted publication output are all very good journals.

longer coverage than other bibliometric databases. Unlike EconLit or SSCI, it features author profiles with very high precision and recall (Baas et al., 2020), which is particularly important for the construction of coauthor networks.

Our networks discount collaborations which are very old. The idea being that coauthor links as conduits of information or influence lose value over time. If two researchers have collaborated in the five years prior to job market year under observation, we include their entire collaboration history. If the last collaboration is older than five years, their coauthor link is discarded. Link weights reflect both decay of the relationship but also frequency of collaboration. The idea behind the weight is that if a pair of researchers have published several papers as coauthors then they have a stronger connection compared to if they had worked together only once. On the other hand, if this collaboration is not recent then the weight reflects this duration.

For each year $t (\in \{2000, 2001, 2002, 2003, 2004\})$ we construct the coauthor network using publications published in all years $1937, 1938, \ldots, t, t+1$. We link two authors m and n upon at least one joint publication published in $t-5, t-4, \ldots, t, t+1$. That is, if the most recent collaboration is older then five years, the link disappears. If there is a recent collaboration however, the link weight is the sum of joint publications, each discounted by the number of years since the publication with an attenuation factor $\delta < 1$: $\sum_p^{P_{mn}} \delta^{t-y_p}$, where P_{mn} is the set of joint publications of m and n, and y_p is the publication year of paper $p \in P_{mn}$. We choose $\delta = 0.95$, thus assuming a low decay of a collaboration relationship. According to our network definition, network variations originate entirely from new connections as well as deprecation and removals of old connections. As the number of articles increases over time, the network grows too. In the earliest of our networks, the one for the year 2000, there are 41,513 distinct researchers. The network for 2004 consists of 52,714 distinct researchers. These networks are represented by symmetric matrices G whose entries g_{mn} indicate the strength of a link between m and n. The diagonal (author's link with herself) is set to 0.

A crucial element in the calculation of author centralities is that we remove the adviser from the network before we compute the adviser's coauthors' Eigenvector centrality. The reason is that our identification strategy exploits *exogenous* changes to the adviser's centrality coming from changes in the centrality of her coauthors. Clearly, we would not want these changes to result from changes in the centrality of the adviser herself.

We only consider the network's giant component. This is the largest sub-network of the coauthor network where each economist is connected to any other economist by an uninterrupted series of coauthor links. Two economists 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 components in our networks cover about one third of the overall network sizes.

In these networks we compute eigenvector centrality as a measure of influence. It is defined as the weighted sum of the Eigenvector centralities of the network neighbors, where the weight corresponds to the neighbor's own Eigenvector centrality. If one is connected to researchers that are themselves more connected then one is more connected. The centrality score is obtained as a fixed point that satisfies, for scalar λ and any non-zero vector $\mathbf{E}$: $\mathbf{E}G = \lambda\mathbf{E}$. By the Perron-Frobenius theorem, if this equation holds then λ is the leading eigenvalue of G, called $\mu_1(G)$, and vector $\mathbf{E}$ is the associated Eigenvector. The elements of $\mathbf{E}$ are hence the Eigenvector centralities of all researchers in G.

In the second part of our analysis we are interested in the connectedness of advisers with potentially hiring universities, rather than with other researchers. We use the Hasselback Faculty Directories for Economics, Management and Finance to obtain information on faculty membership.[18] Faculty rosters for Economics exists for the 2001/2002 and 2003/2004 academic years, for Management for the 2001/2002 academic year, and for Finance for the 2000/2001, 2002/2003 and 2004/2005 academic years. The rosters include 21,079 distinct faculty members with presence in Scopus (which is a trivial necessary condition to be in the coauthor network). 7,013 of them are also members in the coauthor network. For every year, and every adviser in that year, we compute the social distance to all faculty members. Then, for every university-adviser pair in a given year, we pick the minimum social distance amongst the adviser-faculty (of that university) distances as the social distance between the adviser and the university.

The identification here relies on the deaths of members of the network. We collect deaths from the RePEc Deceased Author Information,[19] but mostly from the universities in our sample which we contacted directly via email in spring 2019. We restrict attention to the deaths which occurred between 1999 and 2004, and find 33 deceased network members. Table 8 gives an account of these researchers along with their date of death. We compute the social distance between advisers and possible placement institutes (for the adviser's students) before and after the removal of the deceased authors. An increase

[18]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.

[19]See `https://ideas.repec.org/i/erip.html`.

in social distance thus means that adviser and the placement institute is further away due to the death.

5 Empirical results

5.1 Centrality score and placement score

In this subsection, we want to show that an increase in a student's adviser's eigenvector centrality improves the student's placement. Our data sample for this analysis consists of graduating PhD candidates of Economics from North American Universities as the unit of analysis. Our explanatory variable of interest is the standardized (normalized) adviser's Eigenvector centrality score which is winsorized at the 99 percentile level to avoid extreme values biasing our results (the winsorization affects 10 observations in our sample). The instrument for this variable is the standardized adviser's coauthors' mean Eigenvector centrality score, winsorized at the 99 percentile level (the winsorization affects 9 observations in our sample).

For our analysis, we estimate the following regression equation in a two-stage least-square (2SLS) IV regression where the IV for Standardized Adviser Centrality$_{it}$ is the Standardized adviser's coauthors' mean Eigenvector centrality score$_{it}$:

$$\begin{aligned}\text{Standardized Placement Score}_{it} =& \beta_0 + \beta_1 \text{Standardized Adviser Centrality}_{it} + \\ & \beta_2 Student\_sex_i + \beta_3 \text{PhD School Rank}_{it} + \beta_4 \text{Adviser Controls}_{it} + \\ & \gamma_1 \text{Adviser}_i + \gamma_3 \text{Year of Completion}_i + \gamma_4 \text{Field}_i + \epsilon_{it} \end{aligned} \tag{1}$$

The outcome variable is the standardized placement university score of student i in year of placement t, where the score is computed following the methodology of the Tilburg University Economics ranking but using data from Scopus. *Standardized Adviser Centrality*$_{it}$ is the normalized eigenvector centrality score of student i's adviser at time t. In the 2SLS regression, the exclusion restriction is *Standardized Adviser's Coauthors' Centrality*$_{it}$ which is the normalized mean Eigenvector centrality score over i's adviser's coauthors in the weighted coauthor network for year t, computed in a network without the adviser. As a robustness check, we also use the normalized average centrality score of the adviser's *second* (the coauthors of the adviser's coauthors) neighbors as IV. Our interest is in β_1. We expect β_1 to be positive as this would indicate a positive relationship between adviser centrality and better placement of her students. *Student sex*$_i$ is a binary variable indicating a female student. *AdviserControls*$_{it}$ include the adviser's Euclidean index of citations in t, her sex, her experience and experience squared. *PhD School Rank*$_{it}$ is the rank according to our version of the Tilburg University Economics ranking of the PhD granting school of student i in year t. Table 1 presents some summary statistics. Figure 3 in the appendix presents the distribution graphically. In all specifications we cluster standard errors at the PhD school to allow for unobserved heterogeneity as well as different group sizes.[20] Fixed effects for the year of completion capture 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 1: Summary statistics in the adviser coauthor centrality sample.

	Mean	SD	Min.	Max.
Standardized placement score	3.44	4.33	-0.27	16.83
Standardized adviser centrality	0.26	1.52	-0.17	8.87
Standardized adviser's coauthors centrality	0.11	0.61	-0.17	4.44
Female adviser	0.96	0.20	0.00	1.00
Female student	0.71	0.46	0.00	1.00
PhD school rank	50.67	124.76	1.00	1031.00
Euclidean index	270.81	411.88	2.83	2685.46
Experience	19.92	8.30	3.00	47.00
Experience^2	465.50	373.55	9.00	2209.00
Observations	418			

Table 7 in the appendix presents the result of the first stage regression. The t-statistic of the instrumented variable is 8.47, so that the F-test obtains as $8.47^2 \approx 71$. Table 2 shows the result of the second stage of the 2SLS instrumental regression. Column (1) presents results where the instrument is the normalized adviser's coauthors' mean Eigenvector centrality score, and column (2) presents results where the IV is the normalized adviser's indirect coauthors' mean Eigenvector centrality score (the coauthors of the adviser's coauthors). Both coefficients are statistically significant. Our result indicates that a one standard deviation change in the weighted centrality of the adviser causes, on average, the score of the placement institute to improve by 1.02–0.95 standard deviations. This corresponds to an improvement of about 455–424 ranks of the placement institution. While this may appear to be a huge effect, note that adviser centrality usually does not change by such a large amount. The mean change in adviser centrality (year on year across all advisers in our sample) is 0.02 which is around 0.013sd. This corresponds to

[20] 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.

Table 2: Second stage results of 2SLS IV regression, coauthor sample.

	(1)	(2)
	Standardized placement score	
Standardized adviser centrality	1.022***	0.947***
	(0.000)	(0.004)
Female adviser	−0.218	−0.247
	(0.983)	(0.980)
Female student	−0.221	−0.223
	(0.696)	(0.691)
PhD school rank	−0.00431	−0.00442
	(0.434)	(0.421)
Euclidean index	−0.00107	−0.00129
	(0.850)	(0.823)
Experience	0.0119	−0.00523
	(0.985)	(0.993)
Experience^2	−0.00230	−0.00194
	(0.744)	(0.782)
Constant	3.569	3.839
	(0.632)	(0.585)
Adviser-fixed effects	✓	✓
Field-fixed effects	✓	✓
Placement year-fixed effects	✓	✓
Observations	418	418

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. Standard errors clustered on PhD school.

an improvement in placement rank by about 6 ranks. Thus, there is evidence in favour of our hypothesis that students of well-connected advisers are initially better placed than students of less connected advisers.

5.2 Social Distance and Placement probability

In this subsection, we present another method to show that an adviser's position in the academic network matter for her student's placement. We show that the social distance between an adviser and a university affects the probability of the adviser placing her student at that university. For identification, we use the deaths of economists as exogenous shocks to the social distance in a placement year. The distance between an adviser and a university in the coauthor network represents a noisy measure of the adviser's capability to reduce the information asymmetry problem of the university with regard to the quality of the match between the adviser's student and the university. For this reason, we expect that as the distance between an adviser and a university goes up, the adviser is less likely to place her student at that university.

The unit of observation for this setting are dyads of adviser-university pairs. We look at all possible paths between every adviser and every possible university that satisfies four conditions: a) there is a department rank available for the university or college, b) we know the faculty members from the Hasselback rosters and c) at least one faculty member of the department is in the coauthor network, d) the adviser has placed at least two students in the above universities in our sample. The last condition is to employ adviser fixed effects meaningfully. We find about $588,000$ dyads satisfying these criteria. We then count the number of steps one has to go from adviser a to the closest member of university k (where each step is a coauthor 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. Table 3 presents summary statistics for this sample which we term "adviser distance sample". For $46,910$ of the dyads, the social distance increased due to the exogenous shock of author deaths, sometimes up to 11 steps. The dependent variable ($Placement_{akt}$) is a dummy variable where 1 indicates one of a's students was placed at university k in year t.

We estimate the following regression equation in a logistic regression model:[21]

$$\begin{aligned} Placement_{akt} =& \beta_0 + \beta_1 \text{IncreaseInSocialDistanceAfterDeath}_{akt} + \beta_2 \text{SocialDistanceBeforeDeath}_{akt} + \\ & \gamma_1 \text{PlacementScore}_{kt} + a + \text{PhDSchoolScore}_j + t + \epsilon_{jkt} \end{aligned} \tag{2}$$

We are interested in coefficients β_1 (identified) and β_2 (not identified). 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 $SocialDistanceBeforeDeath_{akt}$ indicates the length of the shortest path between adviser a to the nearest faculty member of k in the coauthor network in year t, given

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

that the path exists, *before* accounting for the change in distance due to the death of authors. Thus, β_2 measures the level effect of the distance between an adviser and a university, whereas β_1 captures the the causal impact of a change in this level. We expect β_2 to be negative since a shorter distance to another faculty should result in a higher placement probability if social connections do play a role in placement. $PlacementSco_{kt}$ is the score according to our version of the Tilburg University Economics ranking of university k in year t. Fixed effects for adviser a and the student's PhD school $PhDSchoolScore_j$ captures the impact of the school rank, while fixed effects for year of placement capture market characteristics for that year.

Table 3: Summary statistics for all continuous variables in the adviser distance sample.

	Mean	SD	Min.	Max.
Student placement	0.0011	0.03	0.00	1.00
Increase in weighted social dist. after death	0.0169	0.43	-7.89	7.50
Weighted social distance before death	4.9783	2.40	0.26	21.00
Euclidean index	162.7873	258.21	0.00	2685.46
Experience	18.3432	8.76	0.00	52.00
Experience^2	413.2086	369.62	0.00	2704.00
PhD school score	2965.2920	2220.69	17.81	8263.46
Placement score	688.5624	1194.01	0.00	8263.46
Observations	588,310			

Notes: All variables refer to time-variant dyads between adviser a and placement k in year t, given that k appears in our ranking and a list of faculty members is available.

Table 4 presents results of the logistic regression indicated by equation 2. In column 1, we have our entire sample. However, we noticed that some placement institutes did not hire a single Economics graduate between 1999-2004 (the time line of our sample). Thus, it is reasonable to drop these institutions as possible placement 'destinations' for the students. Not doing so would underplay the impact of our explanatory variables since it looks like these departments were just not in the market in our time frame. In column 2, we restrict attention to only those placement institutes which hired at least once between 1999-2004. This reduces the number of observations (dyads) to about 440000. Finally, we hypothesize that the impact of an increase in distance may be felt more when advisers were trying to place their students in institutes which are research active (proxied by the institute having a PhD program). This could be because coauthor links are more valuable when both the possible placement institute and the adviser's university are participating actively in research. To test this hypothesis, in column 3, we add another restriction to the data from column 2 - placement institute must have a PhD program. The number of observations for this analysis is about 154,000. As expected, the coefficient of social distance before death is negative and significant in all columns, indicating that students are more likely to be placed at departments to which their adviser has a shorter social distance. A one standard deviation increase in the distance to university k decreases the odds of being placed at k by about $e^{-0.181} - 1 \approx -16.5\%$ (at the mean weighted social distance before death) and holding all other variables fixed at the mean. However, the weighted distance rarely increases by 1sd. The mean of the increase in social distance is about 0.04sd, and this corresponds to a decrease in probability of being placed by around 4%. Also, note that the impact of an increase in social distance is indeed highest in column 3, thereby adding empirical support to our hypothesis that the social distance between an adviser and an institute matters more for the placement of the adviser's student when the institute is research active.

Table 4: Results of a logistic regression for placement probability in adviser distance sample.

	(1)	(2)	(3)
		Student placement	
Increase in weighted social dist. after death	-0.181^{**}	-0.160^{**}	-0.221^{***}
	(0.013)	(0.021)	(0.007)
Weighted social distance before death	-0.156^{***}	-0.119^{***}	-0.134^{***}
	(0.000)	(0.000)	(0.000)
Euclidean index	0.001	0.001	0.001
	(0.296)	(0.299)	(0.491)
Experience	-0.009	-0.005	0.096^{*}
	(0.889)	(0.937)	(0.079)
Experience^2	-0.003^{*}	-0.003^{*}	-0.004^{*}
	(0.070)	(0.067)	(0.082)
PhD school score	-0.0004	-0.0004	-0.001^{**}
	(0.108)	(0.109)	(0.013)
Placement score	0.0003^{***}	0.0002^{***}	0.0002^{***}
	(0.000)	(0.000)	(0.000)
Adviser-fixed effects	✓	✓	✓
Placement year-fixed effects	✓	✓	✓
Observations	588,310	440,617	154,080

Notes: ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. Standard errors clustered on PhD school. All variables refer to dyads between adviser a and placement k in year t, given that k is listed in our version of the Tilburg University Economics ranking and a list of faculty members is available.

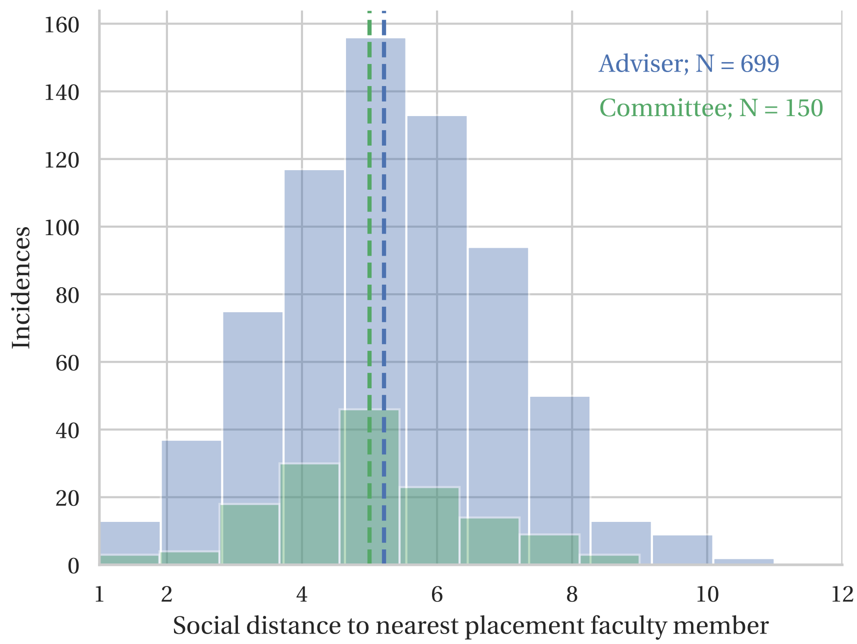
5.3 Channel

Hitherto, we have strived to establish that an adviser's connectedness affects her student's placement. However, we have not shown any formal analysis which explores the channel through which this may happen. Identifying the channel empirically is beyond the scope of this paper. However, in this section we present some supporting evidence to argue that an adviser's connectedness in the coauthor network matters for her student's placement because it reduces uncertainty regarding the match quality of a student with a university. Some other theoretically possible channels include reciprocity and favoritism. We will provide supporting empirical analysis (without claiming any causality) to argue that the latter channels may not be 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 437 non-zero links between universities in our sample (i.e. those that produce and hire PhD students). Of these only 5.1% are bi-directional, meaning both universities. Being very rare, bidirectional links tend to occur more often with top schools, i.a. a student moving from Harvard to MIT and vice verse. This is not only related to size and turnover of the Economics faculty, but also to the presence of business schools, which we don't distinguish here. Based on the low number, we rule out reciprocity as an important channel through which adviser connectedness affects student placement.

We define 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. 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. An example to illustrate social distance - 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 coauthors but one of her adviser's coauthors has a coauthor, the social distance is 2. Figure 1 indicates that out of the 519 advisers for whom we can connect adviser and student's placement faculty members (through some path of coauthors), only 11 times did the student go to her adviser's coauthor's university. So, favoritism towards coauthors is rare. This further strengthens our assertion that indirect connections matter a lot for job placement (over and above direct connections). The mean social distance between an adviser and her student's placement is about 7. The number is exactly the same when including the social distances of PhD committee members (which we know for 109 PhD students). Given the high average social distance between the adviser and the student's placement, we conclude that there is little scope for favoritism.[22]

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



Notes: Histogram shows social distance between a student's adviser/committee members 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 adviser's productivity, age, gender and affiliation, we control for this effect.

6 Conclusion

We show that an increase in a student's adviser's connectedness positively affect the student's placement in the academic market for Economics doctoral graduates. Further, we show that the distance between

[22] 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.

an adviser and a university negatively affects the probability of the adviser placing her student at that university. Our result that the connectedness of the adviser matters for the placement of Economics graduates has insights into the general labor market. 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 - links with more connected workers 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.

Further avenues for research include the quality of a job match. Ultimately, the Economics job market is not about matching the student with the highest ranked department, but to improve the match between the student and the department (Smeets et al., 2006; Chandrasekhar et al., 2020). 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.

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A Appendix

A.1 Additional variable description

The control variables for adviser characteristics include *Euclidean Index*$_t$, *Experience*$_t$, *Experience*^2_t and adviser's gender. The computation of the Euclidean index in t is as follows (as in Perry and Reny (2016)): record the total citations count to each of researcher i's n publications published by t, then take the square root of the sum of the squared citation counts. That is, if $c_{i,k,t}$ is adviser i's total citation count for paper k by period t, then $\text{Euclid}_{i,t}$ of adviser i in t is:

$$\text{Euclid}_{i,t} = \sqrt{\sum_{k=1}^{n} c^2_{i,k,t}} \tag{3}$$

The Euclidean index increases monotonically in the number of publications with positive citation count. *Experience* is the number of years between the adviser's first publication and t. All these variables are computed using data from Scopus obtain through code developed by Rose and Kitchin (2019). The adviser's sex (*Female adviser*) is equals 1 if the student's first name is estimated to be female with probability ≥ 0.5 in the genderize.io database, and 0 otherwise.

Student controls include *Female student*, *PhD School Score*, *Placement Score*, *PhD School*, *Year* and *Field*. *Female student* equals 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 Score* is the score of the student's PhD graduate school according to our version of the Tilburg University Economics ranking in the year she obtained her PhD. The same logic applies to *Placement Score*. *Year* is a dummy variable for the year before 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 JEL category. The last two variables are taken from the annually published lists on dissertations in Economics at North American universities.

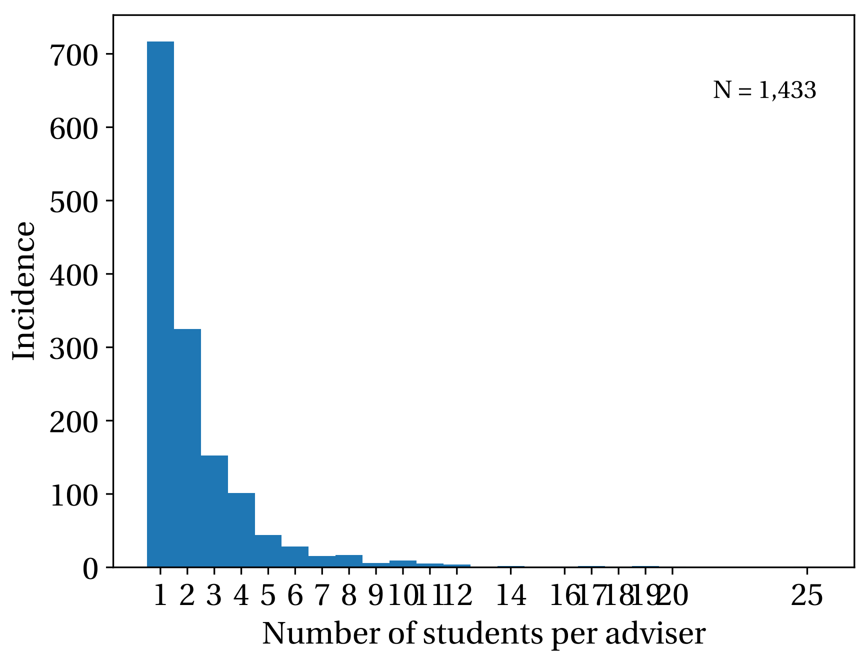
A.2 Additional tables and figures

Table 5: Crosstable by year and JEL code for all PhD students.

JEL Year	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	R	Z	All
2000	0	1	20	34	40	49	34	16	30	39	2	33	5	5	71	9	12	0	400
2001	0	2	50	76	82	99	95	38	55	78	7	67	12	11	94	18	18	0	802
2002	0	3	39	82	79	88	96	22	53	71	4	63	11	10	112	13	22	0	768
2003	1	3	39	93	89	85	79	34	68	63	6	54	9	11	95	13	17	1	760
2004	1	1	31	53	39	64	56	15	37	35	7	33	9	4	48	14	5	1	453
All	2	10	179	338	329	385	360	125	243	286	26	250	46	41	420	67	74	2	3183

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 from JEL general category Q ("Agriculture") are excluded.

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



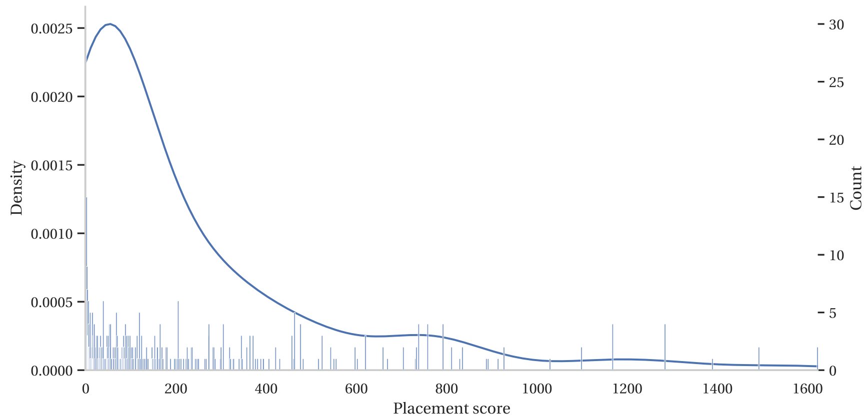
Notes: Histogram shows the number of advisers (y axis) with a given number of students (x axis). Only students with known adviser from North-American universities that graduated in the academic years 2000/2001, 2001/2002, 2002/2003, and 2003/2004 considered.

Table 6: Advisers with most PhD students, 2000-2004.

	Name	Students	School	Citations	Euclid	Experience
1	Daron Acemoglu	25	Massachusetts Institute of Technology	708.0	156.42	10
2	Andrei Shleifer	20	Harvard University	5364.0	1074.77	17
3	Peter C.B. Phillips	19	Yale University	5098.0	1751.34	30
3	Roger R. Betancourt	19	University of Maryland	105.0	35.34	32
5	Olivier Jean Blanchard	18	Massachusetts Institute of Technology	1823.0	597.19	24
6	John Y. Campbell	17	Harvard University	2189.0	505.74	17
6	Lawrence F. Katz	17	Harvard University	1681.0	615.22	22
8	Abhijit V. Banerjee	16	Massachusetts Institute of Technology	674.0	329.04	12
9	Arnold C. Harberger	14	University of California, Los Angeles	88.0	38.29	47
9	Ronald Andrew Ratti	14	University of Missouri	50.0	26.08	26
11	David E. Card	12	University of California, Berkeley	631.0	196.98	21
11	Dominick Salvatore	12	Fordham University	148.0	43.59	31
11	John C. Haltiwanger	12	University of Maryland	520.0	221.28	21
11	Ricardo J. Caballero	12	Massachusetts Institute of Technology	473.0	160.81	14
15	Claudio González-Vega	11	Ohio State University	34.0	24.21	17
15	Gary S. Becker	11	University of Chicago	950.0	331.90	18
15	George W. Evans	11	University of Oregon	344.0	90.00	19
15	James M. Poterba	11	Massachusetts Institute of Technology	1397.0	495.78	20
15	Stephen J. Turnovsky	11	University of Washington	1000.0	153.53	35

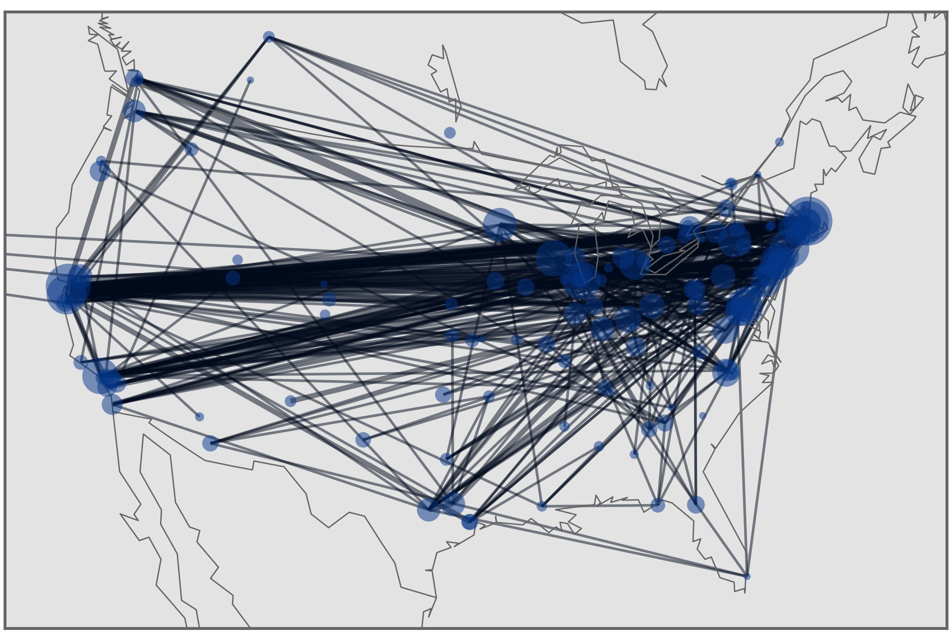
Notes: Table lists PhD advisers by number of PhD students that graduated at North American Economics departments in the academic years 2000/2001, 2001/2002, 2002/2003, and 2003/2004. *Students* is the number of students that graduated with this adviser. *Citations* is the number of citations to that adviser as of 2003. *Euclid* is the adviser's Euclidean index of citations as of 2003. *Experience* is the number of years since the first publication. All information originate from Scopus and were obtained in December 2020. Only advisers with Scopus profile considered. Co-advised students count as full supervised students.

Figure 3: Distribution of placement score of initial placement.



Notes: Graph shows the distribution of the score 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, 2002/2003, and 2003/2004 considered, whose initial placement is ranked in the our version of the Tilburg University Economics ranking.

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, 2002-2003, and 2003-2004. 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.

Table 7: First stage results of 2SLS IV regression, coauthor sample.

	(1)	(2)
	Standardized adviser centrality	
Standardized adviser's coauthors centrality	1.399***	
	(8.47)	
Standardized adviser's 2nd neigh. centrality		2.443***
		(10.19)
Female adviser	−2.245	−2.214
	(−0.76)	(−0.79)
Female student	0.0703	0.0665
	(0.52)	(0.52)
PhD school rank	−0.00171	−0.000461
	(−0.74)	(−0.21)
Euclidean index	−0.00383***	−0.00384***
	(−4.30)	(−4.54)
Experience	−0.247	−0.181
	(−1.28)	(−0.98)
Experience^2	0.00467	0.00346
	(1.40)	(1.09)
Constant	4.107	3.238
	(1.57)	(1.30)
Adviser-fixed effects	✓	✓
Field-fixed effects	✓	✓
Placement year-fixed effects	✓	✓
Observations	418	418

Notes: t-statistics in parenthesis. ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. *adviser's 2nd neigh.* refers to the coauthors of the adviser's coauthors.

Table 8: List of deceased faculty members in the dataset.

Name	Date of death	Name	Date of death
Dalton, George	1999, Aug 23	Bowman, Mary Jean	2002, Jun 04
Liu, Jungchao	1999, Aug 31	Smith, Bruce D.	2002, Jul 09
Griliches, Zvi	1999, Nov 04	Ansoff, H. Igor	2002, Jul 14
Gapinski, James H.	2000, Jan 01	Dornbusch, Rüdiger	2002, Jul 25
Johnson, Byron L.	2000, Jan 06	Ando, Albert	2002, Sep 19
Heyne, Paul	2000, Mar 09	Gabriel, Stuart A.	2002, Oct 15
Miller, Merton H.	2000, Jun 03	Sertel, Murat R.	2003, Jan 25
Lillard, Lee A.	2000, Dec 02	Geisel, Martin S.	2003, Feb 07
Elliott, John E.	2001, Jan 01	Johnson, D. Gale	2003, Apr 13
Cameron, Rondo E.	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 P.	2001, Jun 20	Hsu, Robert C.	2004, Jan 18
Rege, Udayan P.	2002, Jan 01	Wilson, George W.	2004, Jan 20
Straub, La Vonne A.	2002, Jan 24	Lee, Winson B.	2004, Mar 01
Rosenthal, Robert	2002, Feb 07	Laffont, Jean Jacques	2004, May 01
Vilasuso, Jon R.	2002, Apr 27		

Notes: Table lists 33 authors who passed away between summer 1999 and summer 2004 while serving on the faculty of universities as listed in the Hasselback lists.