B Online Appendix

B.1 Further Details on the Data

Rose (2023) uses two partly overlapping datasets curated by the American Economic Association. The first is the December issues of the Journal of Economic Literature, where new Economic dissertations are listed by JEL category alongside their author and the author's university. The EconLit database provides a few corrections, most of which relate to typos. Some dissertations were not listed in the JEL lists but are present in the EconLit, and few corrections to avoid duplicated entries were applied. We use only data for only those students who we can find in both databases, and the corresponding information (after corrections) is available from both the JEL lists and EconLit. Table B1 shows the distribution of students by JEL general category and year of their dissertations.

Table B1: Cross-tabulation of students by year of degree and field.

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	68	9	12	0	397
2001	0	2	50	76	82	99	94	38	55	78	7	67	11	11	94	18	18	0	800
2002	0	3	39	82	78	88	96	22	53	70	4	63	11	10	112	13	22	0	766
2003	1	3	40	93	89	85	79	34	68	64	6	54	9	11	95	13	17	1	762
2004	1	1	31	53	39	64	57	15	37	35	7	33	9	4	48	14	5	1	454
All	2	10	180	338	328	385	360	125	243	286	26	250	45	41	417	67	74	2	3179

Notes: Table lists the numbers of graduated PhD students from North American universities for the academic years 2000/2001, 2001/2002, 2002/2003, and 2003/2004 by JEL general category. Students from JEL general category Q ("Agriculture") are excluded.

The authoritative source for adviser information is the students' dissertations. We find most of them in the ProQuest database. We complement this with an extensive online search in databases (RePEC Genealogy, Academic Family Tree, Mathematics Genealogy Project) and with direct contact[12] with the universities. At the end of this process, we know the adviser for all but 27 students from 18 different universities. Note that this includes students whose dissertations exist, but we are unable to determine the adviser. This could be because the signature in the dissertation is not readable or because ProQuest lists more than 2 advisers and the dissertation acknowledgement cannot resolve who is the main adviser. Table B2 gives an account of the advisers with the most students. When multiple advisers share a student, we count the student multiple times. In Table B1, we show the number of students per

[12] Of 131 contacted departments, 29 sent information, 17 declined to share this information and 10 do not have records from the period 1999-2004. The rest did not answer.

adviser for all known advisers in our time frame.

Table B2: Advisers with most PhD students (academic years 2000/01-2003/04).

	Name	Students	School	Citations	Euclid	Experience
1	Andrei Shleifer	16	Harvard University	5469	1099.60	17
2	Daron Acemoglu	15	Massachusetts Institute of Technology	722	159.52	10
	David E. Card	15	University of California, Berkeley	643	200.33	21
4	Roger R. Betancourt	14	University of Maryland	112	38.08	32
5	Carlos A. Végh	13	University of California, Los Angeles	307	115.65	14
	John Y. Campbell	13	Harvard University	2228	516.03	17
	Peter C.B. Phillips	13	Yale University	5176	1771.50	30
	Ronald Andrew Ratti	13	University of Missouri	52	27.02	26
	Thomas D. Willett	13	Claremont Graduate University	398	91.94	35
10	Arnold C. Harberger	12	University of California, Los Angeles	92	39.83	47
	Dominick Salvatore	12	Fordham University	149	44.37	31
12	Abhijit V. Banerjee	11	Massachusetts Institute of Technology	688	335.69	12
	Michael Grossman	11	City University of New York	939	259.24	29
14	John C. Haltiwanger	10	University of Maryland	528	224.11	24
	Lawrence F. Katz	10	Harvard University	1722	633.56	22
	Olivier Jean Blanchard	10	Massachusetts Institute of Technology	1864	606.88	24
	Richard E. Wagner	10	George Mason University	225	102.77	37
	Robert A. Moffitt	10	Johns Hopkins University	655	145.04	26
	Robert M. Townsend	10	University of Chicago	561	368.18	26
	Samuel Bowles	10	University of Massachusetts	804	276.27	36

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 2022. Co-advised students count as full supervised students.

We retrieve faculty information from various Hasselback Faculty Directories for Accounting, Economics, Finance, and Management. The accounting scholar James R. Hasselback compiles these lists by contacting the relevant department heads. They include all US teaching institutions that offer an Accounting degree, plus a select set of institutions from various countries (mostly Canada and Australia). We use the lists for the following academic years:

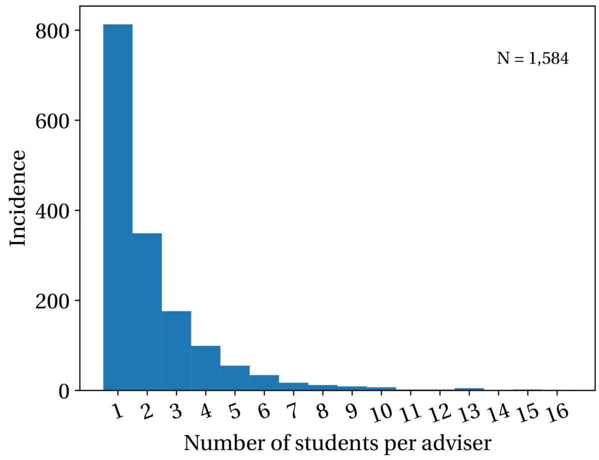
- Accounting: 2000-2001, 2001-2002, 2003-2004[13]
- Economics: 1999-2000, 2001-2002, 2003-2004, 2006-2007
- Finance: 2000-2001, 2002-2003
- Management: 2000-2001

[13] We omit 2002-2003 because the PDF wasn't readable automatically.

From the PDFs, we extract each researcher alongside their academic rank, and leave or visiting statement. This permits us to omit deceased or visiting researchers and emeriti. Some listings are outdated, in which case we omit the faculty information for this year. When a researcher is listed in multiple non-consecutive years at a university, we assume the researcher is also present at the university in the intervening years in which she is not listed in the roster.

We then attempt to match each researcher registered with a PhD to the Scopus database. For this, we use all available information, notably the affiliation and the broad field (Social Sciences). For the relevant years (2000 to 2005) we find 44,591 researchers from 808 distinct institutions. For 3,680 of these, from 739 institutions, we were not able to find a matching Scopus author profile. However, only 7,845 researchers are actually in our coauthor networks.

Figure B1: 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.

B.2 Extensive margin

We would like to test whether adviser centrality affects placement on the extensive margin. The data consists of adviser-university dyads for each year and the outcome variable is a dummy with a 1 indicating a student of the adviser was placed at the university. The main explanatory variable is standardized winsorized adviser centrality (instrumented by standardized winsorized adviser's coauthors' mean centrality). The regression result is presented in table B3. It appears that while adviser centrality affects placement on the intensive margin (section 4.1), it does not have a significant impact on the extensive margin.

Table B3: Probability of placement, distance sample.

	(1)	(2)	(3)	(4)
	Adviser centrality		Student placement	
Adviser centrality		0.020	0.000	
		(0.043)	(0.000)	
Adviser's coauthors centrality	1.283^{***}			-0.000
	(0.194)			(0.000)
Social distance before death	-0.002^{**}	-0.144^{***}	-0.001^{***}	-0.001^{***}
	(0.001)	(0.016)	(0.000)	(0.000)
Citation distance	0.003^{*}	-0.142^{***}	-0.001^{***}	-0.001^{***}
	(0.002)	(0.029)	(0.000)	(0.000)
Adviser Euclid	-0.003	0.000	-0.000	0.000
	(0.002)	(0.000)	(0.000)	(0.000)
PhD school score	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Placement score	-0.000^{**}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Adviser's coauthors centrality × Placement score				0.000^{**}
				(0.000)
Adviser centrality				
Social distance before death		-0.003^{***}		
		(0.001)		
Citation distance		0.003^{**}		
		(0.002)		
Adviser Euclid		-0.002		
		(0.002)		
PhD school score		-0.000		
		(0.000)		
Placement score		-0.000^{***}		
		(0.000)		
Adviser's coauthors centrality		1.267^{***}		
		(0.202)		
Adviser FE	✓	✓	✓	✓
Adviser experience FE	✓	✓	✓	✓
Graduation year FE	✓	✓	✓	✓
N	403,059	393,536	403,059	403,059
# of advisers	531	517	531	531

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. Column (1) presents the first stage results. Column (2) presents the IV Probit results. Column (3) presents the regression output from a 2SLS IV regression where the outcome dummy variable is treated as a continuous variable. Column (4) is a reduced form OLS regression where the IV interactes with the score of the candidate placement university in that observation (each observation is an adviser-university dyad). Adviser centrality is the standardized and winsorized Eigenvector centrality and is instrumented by the standardized winsorized adviser's coauthors' mean Eigenvector centrality.

This is not unexpected. In the distance sample, the unit of observation is adviser-university dyads by placement year. The outcome variable is 1 if the adviser places her student in that university in that year, else it is zero. Thus, for each adviser, in every placement year, the outcome is a vector of 0 (for everywhere the adviser did not place a student that year) and ones. Adviser centrality is an adviser level variable which is common to both the failures (outcome=0) and successes (outcome=1) and is thus not expected to significantly impact the outcome. Furthermore, we control for the distance between the adviser and the potential placement university. These controls will capture some of the effect of adviser connectedness and make it even less likely that adviser centrality remains significant in this regression.

Our previous analysis indicates that higher adviser centrality is positively related to the quality of student placement. To test this idea in the distance sample, column (4) of Table B3 shows the result of a regression with an interaction of our centrality instrument (mean centrality of the adviser's coauthors) with "placement score". Though very small, the coefficient is significantly different from zero, indicating that adviser centrality matters more for getting placed at better ranked departments.

B.3 Adviser centrality's impact on distance

What is the relationship between adviser centrality and the distance (in the coauthor network) between the student's graduating university and the university in which she gets placed? For example, do more connected advisers place their students closer to their own university, e.g., at their coauthor's university, or coauthor's coauthor's university? We find little evidence of this to be the case. Table B4 presents results from a regression where the outcome variable is the distance between the adviser and the university in which her student is placed (in column (1)). The distance between an adviser and a department refers to the length of the shortest path between the adviser and the department in the coauthor network. In column two, the outcome variable is the weighted distance between the adviser and the placement department, where the distance between the two is divided by the number of nodes at that distance (a noisy measure of the strength of the relationship). Thus, while 'closeness' between an adviser and a department does increase the probability of the adviser placing her student at the department (section 4.2), as we can see from Table B4, higher adviser centrality does not significantly affect how close or far the adviser's student gets placed.

B.4 Deaths in centrality data

A possible exogenous shock which could be used for identification in the centrality data is looking at the changes in adviser centrality due to the death of Economists. We take another look at our baseline centrality analysis after constructing a new explanatory variable of interest: change in adviser centrality due to deaths of Economists in the year before graduation of the adviser's students. For every year, we generate two networks - In one network we connect authors based on coauthored papers. The other network is the same, except that we remove nodes for those economists who passed away that year. Then, in both networks, we compute the centrality of each adviser. The difference between the two centralities is the change in the centrality of advisers due to the death of economists. In Column 3 of

Table B4: 2SLS IV regression on distance between placement and adviser, coauthor centrality sample.

	(1)	(2)
	Social distance	
Adviser centrality	−0.432	−0.336
	(0.269)	(0.258)
Adviser Euclid	−0.002	−0.002
	(0.002)	(0.002)
Student female	−0.351	−0.353
	(0.252)	(0.251)
PhD school rank	0.001	0.000
	(0.005)	(0.004)
Constant	3.642***	3.644***
	(0.421)	(0.413)
Adviser FE	✓	✓
Adviser experience FE	✓	✓
Field FE	✓	✓
Graduation year FE	✓	✓
N	426	426
# of advisers	180	180
Effective F	6.8	2.9

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. Adviser centrality is the standardized winsorized Eigenvector centrality. In column (1) the instrument is the standardized winsorized adviser's coauthors' mean Eigenvector centrality, in column (2) it is the standardized winsorized adviser's indirect coauthors' mean Eigenvector centrality.

table B5, we run an OLS where the main explanatory variable is the change in adviser centrality due to deaths. The main explanatory variable is not significant here. One reason for this is that the change in centrality due to only deaths is too small (mean 0.0002 in our regression sample) as compared to changes in centrality due to all other reasons (mean 0.014).

Also, we investigate if a death in the adviser's near neighbourhood (first, second or third neighbour) in the coauthor network influences the placement of her student. To this end, we construct dummy variables indicating whether a first (coauthor), second (indirect) or third neighbour of the adviser died in the period since the last placement year. We control for these variables in our main IV regression. The first and second stage of this estimation is presented in column 1 and 2 of table B5 respectively. While it may be surprising to the reader that deaths in the immediate neighbourhood of an adviser do not affect the placement of her students, these results are driven by the very small number of observations. For example, in our regression sample, there are only 6 advisers who lost a direct coauthor in the period of our observation.

B.5 Close placements

In this subsection, we use our distance data to check if students are more likely to end up in a department where the adviser's neighbours (in the coauthor network) are located as compared to departments which are further from the adviser. In Table B6, we use a dummy variable which indicates that a student is placed in a department which is of distance 3 or less from the adviser in the coauthor network. Column (1) is the baseline case. In column (2) we drop those with distance 1 (thus, now the outcome is 1 if the adviser's student is placed at departments which are at a distance of 2 or 3 from the adviser). In column (3), we further drop those with distance less than 3 respectively. Thus, column 3 tests if a student is more likely to join a department having her adviser's third neighbour as compared to any other department which is more than distance 3 away from the adviser. As is clear from Table B6, we find that a student is more likely to be placed in a school which is closer to the adviser than in one which is further away. Furthermore, the effect is not limited to direct connections. This is evident from column 3.

Table B5: Impact of deaths on placement, adviser centrality sample.

	(1)	(2)	(3)
	Adviser centrality	Placement score	
Adviser centrality		0.822***	
		(0.263)	
Adviser's coauthors centrality	1.415***		
	(0.343)		
Change in centrality due to death			0.103
			(0.157)
Adviser Euclid	−0.005	0.003	−0.002
	(0.004)	(0.003)	(0.003)
Coauthor died	−0.838	1.453	
	(0.828)	(1.194)	
Second neighbour died	0.053	0.821	
	(0.215)	(0.897)	
Third neighbour died	0.023	1.164**	
	(0.229)	(0.589)	
Student female	0.055	−0.611	−0.620
	(0.108)	(0.584)	(0.748)
PhD school rank	−0.002	−0.003	−0.003
	(0.002)	(0.005)	(0.007)
Constant	−14.915	−10.584	12.177***
	(19.625)	(20.869)	(4.304)
Adviser FE	✓	✓	✓
Adviser experience FE	✓	✓	✓
Field FE	✓	✓	✓
Graduation year FE	✓	✓	✓
N	574	574	572
# of advisers		194	193
Effective F		17.0	

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. Column (1) presents the first stage results for column (2). Adviser centrality is the standardized winsorized Eigenvector centrality and instrumented by standardized winsorized adviser's coauthors' mean Eigenvector centrality. In column (3), we regress student placement outcomes directly on the change in the centrality of the student's adviser occurring due to deaths in the network of coauthors.

Table B6: Linear model using binary indication of distance, adviser centrality sample.

	(1)	(2)	(3)
		Placed student	
Distance to placement < 5	0.004***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)
Adviser Euclid	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
PhD school score	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Placement score	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Adviser FE	✓	✓	✓
Adviser experience FE	✓	✓	✓
Graduation year FE	✓	✓	✓
N	406,714	406,714	403,470
# of advisers	532	532	532

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. In column (1), the outcome is 1 if adviser-placement distance<5, else it is zero. In column (2), we drop observations where adviser-placement distance equals 1. Thus, the outcome dummy is 1 if adviser-placement distance is 2, 3 or 4, else it is zero. In column (3), we drop observations where adviser-placement distance<3. Thus, the outcome dummy is 1 if adviser-placement distance is 3 or 4, else it is zero.

B.6 Different experience controls

A possible variation in how we can control for adviser experience affecting placement is to allow for its interaction with adviser productivity as an explanatory variable. In this section, we do this in three ways. One (column (1) of Table B7), we interact the continuous experience variable with the continuous adviser productivity variable (Euclid). Two (column (2)), we divide the Euclid variable into quartile bins and interact this categorical variable with the continuous experience variable. In column (3), we partition "Adviser Euclid" and "Adviser experience" into quartile bins and interact the categories. Table B7 shows that controlling for experience via interactions with productivity does not affect our results qualitatively though the coefficients do change.

Table B7: 2SLS IV regression with experience interaction, coauthor centrality sample.

	(1)	(2)	(3)
	Placement score		
Adviser centrality	0.494	0.560*	0.513
	(0.362)	(0.314)	(0.333)
Adviser Euclid	0.025***	0.001	0.001
	(0.010)	(0.006)	(0.004)
Adviser experience	−0.700	−0.234	0.031
	(0.476)	(0.421)	(0.370)
Adviser experience × Adviser Euclid	−0.001***		
	(0.000)		
Adv. experience^2	0.014	−0.005	−0.004
	(0.011)	(0.010)	(0.009)
Student female	−0.372	−0.384	−0.359
	(0.593)	(0.608)	(0.590)
PhD school rank	−0.001	−0.001	−0.001
	(0.003)	(0.003)	(0.003)
Adviser Euclid quartile=2 × Adviser experience		0.325	
		(0.313)	
Adviser Euclid quartile=3 × Adviser experience		0.499	
		(0.345)	
Adviser Euclid quartile=4 × Adviser experience		0.307	
		(0.489)	
Constant	5.556	9.166	−0.798
	(4.156)	(6.328)	(1.602)
Adviser FE	✓	✓	✓
Field FE	✓	✓	✓
Graduation year FE	✓	✓	✓
N	579	579	579
# of advisers	194	194	194
Effective F	16.3	17.7	17.4

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. Adviser centrality is the standardized winsorized Eigenvector centrality and instrumented by standardized winsorized adviser's coauthors' mean Eigenvector centrality. In column (1), we interact the continuous experience variable with the continuous Euclid variable. In column (2), we divide the Euclid variable in quartile bins and interact this categorical variable with the continuous experience variable. In column (3), we partition "Adviser Euclid" and "Adviser experience" into quartile bins and interact the categorical variables (coefficients suppressed).

B.7 Restricting only to first neighbours

Would we have obtained the same results by focusing only on the direct contacts of the advisor at the time of a student's graduation (instead of accounting for indirect contacts via adviser centrality)? We run our IV regression again, but this time our main explanatory variable is adviser degree (number of coauthors) which is instrumented by the mean degree of the adviser's coauthors. We also run the reduced form OLS with the adviser degree and the mean degree of the adviser's first neighbours as the main explanatory variable. The results are presented in table B8. We have to point out that the IV used in this regression is weak, as is clear from the table. With that caveat, the IV result indicates that "Adviser degree" on its own does not significantly affect placement quality.

Table B8: 2SLS IV and OLS regressions with adviser degree, coauthor centrality sample.

	(1) Adviser degree	(2)	(3) Placement score	(4)
Adviser degree		8.223	−0.104	
		(20.895)	(0.137)	
Adviser neigh. mean degree	−0.050			−0.414
	(0.171)			(0.253)
Adviser Euclid	0.003	−0.024	−0.001	−0.001
	(0.003)	(0.058)	(0.002)	(0.002)
Student female	−0.138	0.511	−0.615	−0.620
	(0.212)	(3.055)	(0.766)	(0.755)
PhD school rank	0.004	−0.032	−0.003	−0.001
	(0.005)	(0.079)	(0.007)	(0.007)
Constant	15.895***	−119.666	13.842***	11.041**
	(3.077)	(334.153)	(5.045)	(4.580)
Adviser FE	✓	✓	✓	✓
Adviser experience FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Graduation year FE	✓	✓	✓	✓
N	574	574	574	574
# of advisers		194	194	194
Effective F		0.1		

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. Column (1) presents the first stage results for the second stage results in column (2). Adviser degree is the standardized and winsorized degree, which we instrument by the standardized and winsorized adviser's coauthors' mean degree. Column (3) presents the OLS result and column (4) presents the reduced form result.

B.8 School rank impact

In this subsection, we delve deeper into the impact (or lack thereof) of school rank on student placement. Tables 3 and 6 indicate that the rank of the graduating student's school is not a significant predictor of student placement. This may come as a surprise. Before doing any further analysis, we want to point out that both these regressions control for adviser fixed effects. In our sample, advisers rarely change schools during the 5 years for which we have data (only 13 advisers changed schools in our regression sample). Thus, since school is essentially a time unvarying characteristic of the adviser (for our sample), some of the PhD school effects is captured via the fixed effects of advisers from that school. Having said that, here we try to understand the impact of school rank on student placement by allowing for more flexible controls for school rank.

The unconditional correlation between placement score and school rank is −0.2234. The negative relationship makes sense, as we expect schools with better ranks (lower) to place their students at better universities. Next, we control for quadratic and cubic polynomials of the PhD school rank. Table B9 presents the results.[14]

Table B9: Polynomial school rank controls, coauthor centrality sample.

	(1)	(2)	(3)	(4)
	Adviser centrality		Placement score	
Adviser centrality			0.690**	0.685**
			(0.298)	(0.300)
Adviser's coauthors centrality	1.336***	1.334***		
	(0.336)	(0.336)		
Adviser Euclid	−0.005	−0.005	0.003	0.003
	(0.004)	(0.004)	(0.003)	(0.003)
Student female	0.071	0.069	−0.571	−0.577
	(0.111)	(0.112)	(0.590)	(0.587)
PhD school rank	−0.002	−0.006	−0.000	−0.012
	(0.002)	(0.004)	(0.013)	(0.017)
PhD school rank^2	0.000	0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
PhD school rank^3		−0.000		−0.000
		(0.000)		(0.000)
Constant	−13.711	−12.137	−11.691	−6.450
	(19.437)	(19.199)	(19.175)	(19.798)
Adviser FE	✓	✓	✓	✓
Adviser experience FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Graduation year FE	✓	✓	✓	✓
N	579	579	579	579
# of advisers			194	194
Effective F			15.8	15.7

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. Column (1) presents the first stage results corresponding to column (3), and column (2) those corresponding to column (4). Adviser centrality is the standardized winsorized Eigenvector centrality. In columns (1) and (3) the instrument is the standardized winsorized adviser's coauthors' mean Eigenvector centrality; in columns (2) and (4) the instrument is the standardized winsorized adviser's indirect coauthors' mean Eigenvector centrality.

[14]We also tried a fourth and fifth degree polynomial in school rank. In both those specifications, the school rank variable remained an insignificant predictor of student placement.

B.9 Match quality

Our analysis so far tests the hypothesis that student placement is positively affected by the connectedness of her adviser. While this is an interesting question, it would be even more interesting to be able to show if the quality of the match between the student and her placement department is better if the student's adviser is more connected. One variable which can indicate match quality is whether the student received tenure at the placement department. Of course, we are cognisant of the fact that tenure decisions are taken a long time after the student is placed and may be affected by many variables which influence the student's tenure candidature during those 6-7 years. Also, we are unable to track some students after the first placement since we don't have their Scopus IDs, and we don't have the second placement for some students, so there is some loss in data points. However, even with these caveats, we believe the reader may be interested in looking at this raw analysis. We run a logistic regression asking whether the student remains at her first placement 6 or 7 years after getting placed there. Note that this is a noisy indicator of tenure (we don't observe if the student received tenure). The explanatory variable of interest is adviser centrality at the time of graduation. The results presented in Table B10 show that higher adviser centrality is not a significant variable in determining tenure in most specifications. Thus, it appears that while an adviser's connectedness may help a student get a better job, whether the student manages to retain the job appears to be up to other forces. Note that when a student does not remain at her first placement six/seven years after joining, this could be because she has moved to a worse-ranked place or a better-ranked one. We investigate this question next.

We check the quality of the match further by testing how adviser centrality affects the difference between the ranks of the first and second placement of those students who changed academic institutions within the first 7 years of getting their first placement. The idea is to see if the connected advisers are 'over-placing' (if the student's second placement is ranked worse than her first placement) or 'under-placing' (if the student's second placement is ranked better than her first placement) their students. We restrict our attention to students who changed jobs within the first 7 years to focus on those graduates who possibly did not get tenure at the department in which they received their first job.

We look at two outcome variables. The first is a dummy variable, which takes the value 1 if the student's second placement is worse ranked than her first placement. The second outcome variable we consider is 'Rank difference' which is the rank of the second placement minus the rank of the first placement. A positive and large rank difference indicates that the second placement was much worse

Table B10: Logistic regression on match quality, coauthor centrality sample.

	(1)	(2)	(3)	(4)
	Same affiliation 6 years later		Same affiliation 7 years later	
Adviser centrality	−0.123	0.026	−0.105	0.029
	(0.193)	(0.056)	(0.160)	(0.052)
Adviser Euclid	−0.002	−0.000	−0.002	−0.000
	(0.003)	(0.000)	(0.003)	(0.000)
Student female	−0.474	−0.006	−0.217	−0.138
	(0.447)	(0.167)	(0.379)	(0.177)
PhD school score	−0.001	0.000	−0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Placement score	0.000	−0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	15.206	1.651**	8.646**	1.726**
	(12.168)	(0.839)	(4.231)	(0.724)
Adviser FE	✓		✓	
Adviser experience FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Graduation year FE	✓	✓	✓	✓
N	305	970	312	949
# of advisers	92	616	94	609

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. Table reports results from second stage only. Columns (1) and (3) control for adviser fixed effects, whereas columns (2) and (4) do not allow more observations.

ranked than the first placement. The results are presented in table B11. We find that adviser centrality does not significantly influence whether a student is over-placed or under-placed (column (1)). However, it does appear that more connected advisers over-place their students by a smaller margin than less connected advisers (column (2)). This poses an interesting avenue for future research.

Table B11: 2SLS IV regression on second placement, coauthor centrality sample.

	(1) Second plc worse than first	(2) Rank difference
Adviser centrality	0.079	−53.652
	(0.078)	(67.624)
Adviser Euclid	0.002***	0.756**
	(0.001)	(0.367)
Student female	−0.081	−248.986***
	(0.137)	(84.135)
PhD school score	−0.000	0.968**
	(0.000)	(0.494)
Placement score	0.000***	0.228**
	(0.000)	(0.104)
Constant	−1.024	3788.264***
	(2.538)	(666.014)
Adviser FE	✓	✓
Adviser experience FE	✓	✓
Field FE	✓	✓
Graduation year FE	✓	✓
N	232	189
# of advisers	140	123
Effective F	2.4	0.9

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

Notes: Standard errors are clustered around adviser and PhD school. Standard errors in parentheses. We look at students who got a second placement 7 years of their first placement. "Rank difference" is the rank of the second placement minus the rank of the first placement. "Second plc worse than first" is a dummy variable which takes the value 1 if the rank of the second placement is worse than the rank of the first. "Adviser centrality" is the adviser's standardized and winsorized adviser's Eigenvector centrality and instrumented by the standardized and winsorized adviser's coauthors' mean Eigenvector centrality. Table reports results from second stage only. Effective F is the Montiel Olea and Pflueger (2013) effective F statistic for weak instruments estimated.