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Employers' networks and employees' productivity: An application to PhD students' outcomes

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Abstract

Are PhD students who are hired from a supervisor's network, on average, more productive? We examine this question using data on 4,666 PhD students who graduated at two major Swiss universities during 2000-2008. We verify that students who had obtained their master's at one of the universities with which her supervisor's coauthors are affiliated, are on average, more productive than the other supervisor's students. This result is robust to including fixed-effects for the universities in which a student had previously studied, various measures for the specialization areas of these universities, and to an instrumental variable approach that accounts for potential omitted variable bias. We take our result as evidence that selecting students from a network of universities with whom supervisors collaborate allows them to deal with market imperfections and select PhD students that are highly productive. Jelcodes:D83,D

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Abstract

Are PhD students who are hired from a supervisor's network, on average, more productive? We examine this question using data on 4,666 PhD students who graduated at two major Swiss universities during 2000-2008. We verify that students who had obtained their master's at one of the universities with which her supervisor's coauthors are affiliated, are on average, more productive than the other supervisor's students. This result is robust to including fixed-effects for the universities in which a student had previously studied, various measures for the specialization areas of these universities, and to an instrumental variable approach that accounts for potential omitted variable bias. We take our result as evidence that selecting students from a network of universities with whom supervisors collaborate allows them to deal with market imperfections and select PhD students that are highly productive.

1 Introduction

"I always have difficulty evaluating the CVs of Italian students: all of them graduate from their schools with 110/110 cum laude."

(A professor from EPFL, 2012)

Every employer is faced with the problem of screening job applicants and hiring the ones with the highest expected productivity (Cornell and Welch, 1996). One difficulty they have is determining which job applicants possess what Arrow (1972) refers to as the "unobservable habits of action", which favor good performance in skilled jobs and include characteristics such as steadiness, punctuality, or initiative. The asymmetries of information employers experience when hiring applicants and the related costs incurred to solve them have been advocated by economists as explanations for why employers rely on employee referrals (Saloner, 1985; Montgomery, 1991), or discriminate against minorities of which they possess little information (Calorimis et al., 1994; Cornell and Welch, 1996). Thus, even though employers may not have initial preferences for job to whom candidates they have been referred or for members of their own social group (Becker, 1957), they might hire them because they know them better.

In this study, we attempt to verify whether PhD students who have obtained their master's from a university from which a supervisor draws her coauthors are, on average, more productive than the other supervisor's students. We define the net of universities from which a supervisor draws her coauthors as the supervisor's "research network" and hypothesize that a supervisor can acquire information about the expected productivity of PhD applicants coming from a given university through her collaborations with coauthors affiliated with that university. Hence, for these students, she can better assess their expected productivity and select the most promising ones.

We address our research question using a novel dataset of 4,666 PhD students in science or engineering who had graduated at two major Swiss technology institutes: the Swiss

Institute of Technology of Lausanne (EPFL) and the Swiss Institute of Technology of Zurich (ETH). As the quote above suggests, academic supervisors, like any employer, are faced with the problem of evaluating the expected productivity of PhD applicants, and it is in their interest to select highly productive candidates, given that they represent an important input to the supervisor's research production (Stephan, 2012; Woolston, 2003).

For our analysis, we derive detailed biographical information on PhD students from their dissertation and Human Resources' files. We then match this information with the publication records of the students and collect fine-grained data on their supervisors. Having measured student productivity with the count of scientific articles students had published during their PhD programs, the box plots in Figure 1 show that students who belong to a supervisor research network are, on average, more productive. Yet, there are several factors, that are correlated with the supervisor's research network and the student's productivity, which might be responsible for the correlation we observe. Our challenge then becomes to identify network effects on student productivity.

In our baseline analyses, we control for factors that are deemed to affect a student's productivity, including gender, age, the quality of a student's past affiliation, a professor's productivity, and access to funding. Moreover, we have measures for social proximity, such as indicator variables for whether a student and a supervisor have the same nationality, or whether the student had studied at any of the supervisor's past affiliations. The resulting evidence points to a strong, positive correlation between having obtained a master's degree at a university from which a supervisor derives her coauthors and a student's productivity.

We estimate several alternative empirical models to confirm this relationship. First, we include supervisor fixed effects, as well as fixed effects for the universities from which the students had obtained their master's degree. The relationship holds, and the magnitude of the coefficient suggests that belonging to the research network of a supervisor increases student productivity by about 11 to 21 percent, depending on the regression specification. Second, we introduce a variable that measures the relevance of a student's master's university to the research pursued by her supervisor. This variable is defined as the number of times a supervisor cites in her articles authors affiliated with the same university as the one from which her PhD student had obtained her master's. The aim is to be able to assess the impact on student productivity of belonging to the research network of a supervisor, holding constant the research specialization of the student's past affiliation. With this measure, the magnitude of the effect of belonging to a supervisor's research network declines, as expected, but remains highly significant. Third, we eliminate from the sample those students who had obtained their master's at the same university as their current affiliation. These students appear to belong to the research network of their supervisors in the vast majority of the cases, which is because supervisors have a substantial fraction of their coauthors affiliated with their own university. However, for these students, we have strong prior that the dynamics through which the supervisor acquires information on their research aptitude involve her net of coauthors only minimally. With the new sample definition, belonging to a supervisor's research network increases student productivity to about 14 to 23 percent.

As an additional test, we estimate an instrumental variable (IV) regression model to deal with possible, time-variant unobservable supervisor or student characteristics, which we could not observe, but were detected by the supervisor. We use as an instrument the share of coauthors from a university with which a student was previously affiliated, of a professor who works in a discipline as distant as possible from that of the student's supervisor. To choose among professors who appear to have the same "discipline distance" from a supervisor, we apply the criterion that the professor we associate with the supervisor has to have the highest number of past affiliations in common with the supervisor. The identifying assumption is that the research network of a scientifically distant professor should be uncorrelated with unobservable characteristics of the student's supervisor, her laboratory, or the type of PhD applicants the supervisor interviews. However, the instrument should be correlated with the research network of the supervisor, and thus with our endogenous variable via the past affiliations the supervisor and her match have in common. The IV estimates deliver a larger coefficient for our variable of interest, which continues to have a statistically significant effect on student productivity. As in the case of Guiso et al. (2009) and Munshi (2003), we speculate that an increase in the coefficient might be determined by the type of omitted variables we encounter in our models or by measurement error. Yet, there is also a possibility that our instrument is not orthogonal to having graduated from a university that belongs to a supervisor's research network, but picks up a set of factors that might affect student productivity.

Analyzing the role of belonging to a supervisor's research network on PhD students' productivity is particularly relevant, given the contributions of PhD recipients to knowledge and technology transfer (Dasgupta and David, 1994; Stuen et al., 2007; Black and Stephan, 2009). Previous studies on PhD students have examined the determinants of PhD productivity, such as faculty quality (Waldinger, 2010) or the organization of knowledge (Conti et al., 2012). Others have investigated the difference in the productivity of domestic versus foreign PhD students, and found that foreign students tend to perform better than domestic ones (Stuen et al., 2007; Gaule and Piacentini, 2012). In their analysis on Chinese students who had obtained their PhDs in the US, Gaule and Piacentini (2012) suggest that Chinese students might be more productive than domestic students, either because they are selected from the best schools, or because they have a higher preference for academic jobs, or because they have a cultural predisposition for higher effort at work. While suggestive, these explanations are not empirically tested.

The work closest to ours is that by Hegde and Tumlinson (2012), which examines the role of ethnic proximity in the context of venture capitalists-startup pairs. The authors show that ethnic proximity between venture capital partners and startup executives is an important predictor of the probability that venture capital companies will invest in startups, and it is positively correlated with startup performance. In contrast to this study, ours uses a different measure of proximity, conducts analyses focusing on PhD students, and controls for selection issues when addressing the impact of belonging to a supervisor's research network on PhD student productivity.

Finally, if we view membership to a network as an aspect of cultural similarity, then our work contributes to the literature on culture and economic outcomes (Guiso et al., 2009; Greif, 1993; Bottazzi et al., 2007; Munshi, 2003). The leitmotiv of these studies is that cultural similarity attenuates problems of asymmetric information and enhances trade (Guiso et al., 2009; Greif 1993); induces venture capital investment (Bottazzi et al., 2007); and increases the likelihood of being employed and the relative pay (Munshi, 2003). A notable exception is represented by Huang et al. (2010), who show that firms in China owned by foreign, ethnically Chinese companies do not outperform firms owned by foreign, non-ethnically Chinese companies. With these findings, the authors show that cultural proximity might also trigger negative outcomes, which, in such a case, they identify as an under-investment by ethnically Chinese companies in firm attributes that enhance performance.

2 Data: PhD students at ETH and EPFL

Our empirical context for analyzing the impact of belonging to a supervisor's research network on student productivity is PhD students from EPFL, Lausanne, and from ETH, Zurich. These universities are the two Federal Institutes of Technology of Switzerland. While EPFL is located in the French-speaking part of Switzerland, ETH is in the German-speaking part. EPFL and ETH are responsible for a large part of the research in science and engineering produced in Switzerland, and they host the largest doctoral programs in these disciplines. ETH is associated with 21 Nobel Prize winners, who at the time of their awards, were engaged as professors at ETH, or had researched there. Both universities are very active in publishing their research: publication data retrieved from Scopus reveals that, in 2011, EPFL and ETH had produced approximately 6,000 articles in science and engineering. EPFL's and ETH's scientific achievements have been recognized in many international rankings: as of today, these universities have held a high ranking in the fields of engineering, technology, and computer science, according to the ranking of world universities by Shanghai Jiao Tong University. Regarding their doctoral programs in 2011, EPFL and ETH hosted 60% of the PhD students in science and engineering enrolled in Switzerland.

From the population of PhD students, we select a sample of 4,666 PhD students who had graduated at EPFL and ETH during the 2000-2008 period. The reason for selecting this sample period is that the universities' Human Resources had extensive biographical information for the students who had graduated during this time window. We complement information from Human Resources with that extracted from student dissertations. We match this information with student publication records, using Scopus. We also collect fine-grained data on student supervisors. These are 559 professors who had supervised, eight on average 8 PhD students during 2000-2008.

Thirty-six percent of the PhD students in our sample were affiliated with EPFL, while the remaining were affiliated with ETH. While for EPFL, we had selected all of the students who had graduated during our sample period, for ETH we considered a fraction, which we obtained by randomly selecting a sample of supervisors per each department and including their PhD students. The distribution of students between the two universities reflects the fact that ETH is a much larger institution than EPFL. To illustrate this idea, in 2008, 645 students had graduated from ETH, whereas 268 had graduated from EPFL. When classified by discipline, 14% of EPFL PhD students are in computer science, 39% in engineering, 4% in life science, and the remaining are in basic science. As for ETH, 6% of students are in computer science, 42% in engineering, 13% in life science, and 39% are in basic science.

PhD students at EPFL and ETH usually complete their PhDs within four years. Extensions are possible, but they tend to be no longer than six months. PhD applicants must have already obtained their master's degree. Hence, they dedicate most of their time to research rather than to taking courses because they have already taken most of them during their respective master's programs. Another important feature of the PhD program is that once applicants are admitted to the doctoral program by a professor, they work with that professor for the entire duration of their PhD program. Discussions with administrative personnel at EPFL and ETH confirmed that switching to another supervisor is rare. Finally, PhD students are considered as employees of the Swiss Confederation and are ensured a salary for the entire duration of their PhD program. We suspect that this last aspect is, in part, responsible for the low dropout rate among EPFL and ETH students, which is around 10% for both universities.

Of the PhD students in our sample, 41% had obtained their master's from the university with which they are currently affiliated. The percentage is equal to 33 at EPFL, and 46 at ETH. Moreover, the percentage of EPFL students who had obtained their master's from ETH is 5, while the percentage of ETH students who had obtained their master's from EPFL is 2.

In general, EPFL and ETH are multi-cultural environments, where PhD students come from a variety of countries and academic institutions. This is partly the result of the high-quality research that is pursued at these universities, and of the high salaries that are offered to PhD students, compared to other countries. The percentage of foreign students at EPFL is 65, while the percentage at ETH is 52. Foreign students come from 576 different universities. Not surprisingly, French PhD students constitute the largest foreign group at EPFL: almost 14% of all PhD students have French nationality. Similarly, German PhD students are the largest foreign group at ETH, representing almost 26% of the total PhD students. Non-European students constitute a small minority at both schools. For instance, North American students represent about 1.5% of total PhD students at each school, while Chinese and Indian students, together, represent about 3%. We suspect that the small percentage of non-European students is due, in part, to the difficulty for non-European students in obtaining working visas to stay in Switzerland after their PhD.

Regarding the supervisors, about 56% of them are foreign at EPFL, while at ETH, the percentage of foreign professors is 38%. The largest foreign group at EPFL is composed of German professors, who represent 11% of total foreign professors. As for ETH, German professors also constitute the largest foreign group, representing 26% of the total foreign professors.

3 Research network and PhD student productivity

In this section, we verify whether students who had obtained their master's from a university that belongs to the research network of their supervisor are more productive than the other supervisor's students. We measure student productivity by a count of the scientific articles a student had published during her PhD program. We adopt a broad definition of scientific articles and include papers published in conference proceedings because an important fraction of our students are computer science and in the electrical engineering fields; in these fields, conference proceedings have at least the same importance as journal articles [1]. Hence, we count the student's publications from the moment the student enters the doctoral program to one year after her graduation. This specification takes into account the fact that there are lags between the time a student ends a research project and the time at which the results of the project are published (see, for example, Arora and Gambardella, 2005). Figure 2 displays the distribution of PhD students by the number of articles they have published. As shown, a large fraction of the students, about 85%, had at least one publication, and 75% had more than one. The average student publication count is very similar for EPFL and ETH: 4.61 for EPFL and 4.75 for ETH. By discipline, the average count of student publications is 5 in computer science and basic science, and 4 in engineering and life science.

⟨ Insert Figure 2 about here ⟩

Our predictor of interest is a measure of student affiliation to the research network of a supervisor. This measure, which we denote as *Belong to prof′s research network*, is an indicator that takes the value of 1 if a student had obtained her master's at one of the universities from which her supervisor draws her coauthors. We built this measure by searching for the academic institutions with which supervisor j's coauthors are affiliated and comparing them with the universities from which j's students had obtained their master's. Data on coauthors' affiliations are available from Scopus. For each student i's affiliation, the relevant comparison is with the affiliation of supervisor j's coauthors, who had written scientific articles with j up to the student's year of entry into the doctoral program. We only consider those coauthors who fall into the last three quartiles of the supervisor's distribution of coauthors. By applying this cutoff, we want to exclude coauthors who, having collaborated only sporadically with supervisor j, cannot be very informative of the research aptitude

[1] We refrain from weighting each publication by its impact factor because conference proceedings rarely have an associated impact factor.

of master's students coming from their university. The percentage of students who had obtained their master's degree from a university with which supervisor j's coauthors are affiliated is 63 at EPFL, and 71 at ETH. When we restrict the sample to students who did not obtain their master's degree from the same university with which they are currently affiliated, the percentage drops to 45 at EPFL, and to 48 at ETH.

We estimate a quasi-maximum likelihood conditional fixed-effects Poisson model, given that our measure for student research productivity can only take positive and integer values (Hausman et al., 1986) . This model has several desirable properties, including consistency of the coefficient estimates and consistency in the standard errors (Wooldridge, 1997). Hence, we estimate the following equation:

$$E(Productivity_i) = \exp(\gamma_0 + \gamma_1 Belong\ to\ prof\ 's\ research\ network + \gamma_2 C_{prox} + \gamma_4 C_{PhD} + \gamma_5 C_S) \tag{1}$$

To capture the effect of belonging to the research network of a supervisor, we need to control for factors that are correlated with our research network dummy and are likely to affect student productivity. To this end, we include three sets of controls. The first set, C_{prox}, includes three measures for the social proximity between a student and her supervisor. The first measure is a dummy variable that is equal to one if the student and the supervisor have the same nationality. We denote this variable as: *Prof & PhD have same nationality.* The second measure is a dummy variable equal to 1 if the student had obtained her master's in one of the universities with which her supervisor was previously affiliated. We label this variable as *Prof & PhD come from same univ.* The logic for including these two variables is that a supervisor is more informed about the research quality of academic institutions located in her country of origin or with which she was previously affiliated; hence, she can more accurately assess the research aptitude of master's students coming from either her own country or from one of her past affiliations, independent of her network of coauthors. There are additional reasons for including these controls. One of them is that working with socially close students might reduce communication costs (Ibarra, 1992; McPherson et al., 2001), with a resulting positive impact on the producivity of the student. Finally, the last measure is defined as the percentage of students from j's group who have the same nationality as i. The idea here is that by being exposed to the nationality of a given student via past hires, the supervisor becomes socially close to that student and can more accurately assess her research aptitude or better communicate with them. We denote this variable as % of *Prof PhDs with same nationality as PhD i*.

C_{PhD} is a matrix of controls related to PhD student i. The included variables are standard controls deemed to affect the productivity of a PhD candidate. Hence, K_{PhD} encompasses student age (*Student age*) at the time of entry into the PhD program, as previous studies have shown that there is a negative correlation between age and research productivity (Conti et al., 2011; Levin and Stephan, 1991). It also includes a dummy, *Gender*, which is equal to one for female gender. In line with previous studies (see, for instance, Long, 1990, or Ding et al., 2006), we suspect gender differences in the production of scientific articles. Moreover, the matrix includes a dummy, *Master's at same univ as PhD*, which is equal to one if the student had obtained her master's degree at the same university as her current affiliation. We suspect that this indicator might be correlated with the productivity of a student in two opposing ways. On the one hand, it is possible that, due to the information asymmetries a professor faces in selecting a student who comes either from abroad or from a different university than her own, she might end up selecting students of low quality, on average. However, it is also possible that, because of these asymmetries, the professor will not hire a student from any of these categories unless the student's expected research aptitude outweighs the screening costs incurred by the supervisor. We control for certain aspects of a student's quality that a professor can verify by examining the student's curriculum. For instance, we count the number of publications the student had published in the two years prior to the start of her doctoral program. This variable, which we denote as *Pre-sample student pubs*, is meant to capture the research skills of the student at the time she applies for a PhD. We include fixed effects for the country in which a student had obtained her master's, as there might be some countries with better educational systems than others, which might be reflected in a student's aptitude. Additionally, these indicators might capture the average supply of students that come from a given country. We include a measure for the average quality of the university where a student has obtained her master's degree, *Ranking of master's university,* which corresponds to the ranking assigned to that university by the QS World University Rankings. Additionally, we use a dummy, *Ranking of master's university (by field)*, which is equal to one if the university from which the student had obtained her master's degree is in the top 50 universities for the research area in which the student is specialized, according to the QS World University Rankings. We consider the following fields: engineering, computer science, and basic sciences. This measure controls for the quality of the university from which the student had obtained her last degree, for the discipline in which she is specialized. As an additional measure for the university quality of the student, we construct a count of the publications the university had produced in the research area of the student. We collect this information from the Scopus publications' database. In this case, we consider a more fine-grained list of fields, which are: physics, mathematics, chemistry, engineering, material science, life science, and computer science. We denote this variable as *Pubs stock of master's university (by field).* We include university-department fixed effects, as there are likely to be differences in the publication patterns of PhD students across departments (Stephan, 2012) and also across universities. Finally, we control for year fixed effects, and the year we consider is that of student i's entry into the PhD program.

C_S is a matrix of controls for supervisor j that are deemed to affect the productivity of student i. We follow Levin and Stephan (1991) and include the age of a professor at the time her student begins the doctoral program. We denote this variable as *Prof Age.* In line with previous studies that have assessed the impact of faculty knowledge capital stock on PhD student outcomes (Waldinger, 2010), we include the professor's stock of publications in the five years prior to the year in which a student begins her PhD program. We denote this variable as *Pre-sample prof pubs.* We also include as controls the number of a supervisor's coauthors (*N of prof coauthors*) and the number of different institutions from which the supervisor draws her coauthors (*N of institutions of a prof's research network*). Both these variables are expressed in the natural logarithm. These variables were built by analyzing the affiliations, as reported by Scopus, of each supervisor's coauthors. The reason why we include them is that they might be correlated with some aspects of the supervisor's knowledge capital stock, and hence, with student productivity, *and* with the probability that a student had obtained her master's at a university from which the supervisor draws her coauthors. We (reasonably) suspect that this probability is an increasing function of the number of coauthors a supervisor has and the number of universities with which they are affiliated. Previous studies have shown a positive impact of grant money on scientific productivity (Ganguli, 2011). In line with these studies, we include the amount of basic research grants (in thousands of real Swiss Francs) the professor had obtained during the period in which she had supervised student i. This amount is averaged over the duration of the student's PhD program. We denote the variable as *Grant amount*. Finally, we also control for the size of a supervisor's PhD group at the moment a PhD student enters the group (*Size of PhD group*). Descriptive statistics of the variables used are reported in Table 2.

The regression results for equation 1 are presented in Table 3. The first column displays the baseline results with university-department fixed effects. The coefficient of the variable, *Belong to research network*, which is equal to 1 if a student belongs to the supervisor's research network, is positive and statistically significant at the 1% confidence level. The magnitude of the coefficient suggests that belonging to the research network of the professor increases student productivity by about 15%. The indicator dummy *Prof & PhD have same nationality*, which is equal to 1 if a student and her supervisor have the same nationality, and the percentage of a supervisor's student of the same nationality as i, *% of Prof PhDs with same nationality as PhD i,* do not seem to have a significant effect on student productivity. Surprisingly, the dummy *Prof & PhD come from same univ* has a negative and statistically significant coefficient, although significance is only at the 10% confidence level. One reason might be that when a professor moves to a university, she might bring her students from her previous affiliations, independent of their productivity. As for the other controls, we highlight some results of interest. For instance, the age of a student and female gender are negatively correlated with student productivity. On the contrary, having scientific publications prior to starting a PhD is positively associated with student productivity. Similarly, the stock of a supervisor's publications, her number of coauthors, and the number of different institutions from which she draws her coauthors are all positively associated with student productivity, suggesting that the latter might benefit from the knowledge capital of a supervisor. Finally, in line with findings by Levin and Stephan (1991), supervisor age is negatively correlated with student productivity.

There are a few reasons to worry about the equation specification above. The first is that we might not be capturing some supervisor characteristics, that are likely to be correlated with the error term, or we may be measuring them with error. To deal with this problem, we estimate a variant of equation 1 in which we exclude supervisor time-invariant characteristics and include supervisor fixed effects. The results are presented in the second column of Table 3. When adding supervisor fixed effects, we notice that the coefficient of the variable *Belong to prof's research network* declines from 0.14 to 0.10, as expected, but remains highly significant. Moreover, the coefficient of the indicator variable, *Prof & PhD come from same univ*, is no longer statistically significant. This suggests that this last variable is correlated with some time-invariant supervisor characteristics, and once we control for these, the impact on student productivity becomes insignificantly different from zero. Interestingly, the sign of the coefficient for the stock of a supervisor's publications now becomes negative and remains highly significant.

A possible objection to the results we have shown above is that the positive correlation between belonging to a supervisor's research network and student productivity is the result of having measured the quality of a student's university with error. Ideally, we want to be able to assess the impact on student productivity of belonging to the research network of a supervisor, *holding constant university quality.* In practice, it is likely that our variables might not entirely capture the quality of a university. Hence, we estimate a variant of equation 1 in which we include fixed effects for the universities where the students had obtained their master's. We strongly doubt that, for the short period we consider, the quality of these universities have significantly changed over time. The results are displayed in column

III of Table 3. The coefficient of our variable of interest, *Belong to prof's research network*, remains significant at the 1% confidence level, and its coefficient increases in magnitude, from 0.14, in column I, to 0.19, in column III. The increase in the coefficient's magnitude suggests that our student-university dummies might capture some (initially) omitted factors, in addition to university quality, that are negatively correlated with student productivity. In column IV, we include both student-university and supervisor fixed effects, and the coefficient of *Belong to prof's research network* remains statistically significant at the 1% confidence level, with a magnitude of 0.12.

While student-university fixed effects are a strong control for the average characteristics of a university, these characteristics might vary significantly by research area. In our regressions, we have included so far controls for the quality of a university in the areas of specialization of a student, but these might not be enough. Without accurate measures for the relevance to a supervisor of the research conducted in the universities from which her PhD students had obtained their master's, it is very likely that our variable of interest, *Belong to prof's research network*, is correlated with the error term. In fact, it is possible that a professor establishes contacts with universities that are particularly relevant for her field of research, *and* independent of her contacts, she hires students coming from these universities because they are specialized in her research field. To address this concern, we built a variable, which is defined as the number of times supervisor j cites in her articles authors affiliated with the same university as the one from which student i had obtained her master's (*N times master's university is cited by prof*). Hence, associating this count to each student's past affiliation should give a strong indication of the relevance for a supervisor's research of that affiliation. The results are reported in the last four columns of Table 3. As before, column V presents the baseline regression results, column VI includes supervisor fixed effects, column VII includes student-university fixed effects, and column VIII encompasses both supervisor and student-university fixed effects. As expected, the coefficient of our variable, *N times master's university is cited by prof*, has a positive and statistically significant impact, regardless of the regression specification used. Not surprisingly, when we control for both supervisor and student-university fixed effects, the variable's coefficient becomes significant at the 10% confidence level, from an initial level of 1%. Once we include our control, the magnitude of the indicator variable, *Belong to prof's research network,* declines but continues to remain highly significant. For instance, in column V (baseline specification with the control *N times master's university is cited by prof*), the magnitude of the coefficient appears to be 0.13, compared to 0.14 in column I (baseline specification without the control *N times master's university is cited by prof*). Overall, these results suggest that, even after controlling for the relevance of a student's affiliation to a supervisor's research, our measure for belonging to a supervisor research network remains positively correlated with student productivity.

⟨ Insert Table 3 about here ⟩

Another concern is that in the case of students who obtained their master's degree at the same university as their supervisor, the indicator variable for whether the student belongs to the research network of the supervisor is one in the vast majority of cases (99%). However, as we already mentioned, for these students, it is very likely that the dynamics through which the supervisor acquires information on their research aptitude involve her net of coauthors only minimally. Hence, to assess the impact of belonging to a supervisor's research network, we restrict the sample to PhD students who had obtained their master's degree at a university different from their current one. The results are displayed in Table 4. We replicate the regression specifications we presented in Table 3. Hence, column I presents the baseline results; column II includes supervisor fixed effects; column III includes student-university fixed effects; column IV encompasses both supervisor and student-university fixed effects; finally, the last four columns present results for the same equation specifications as in the first four, but include the control *N times master's university is cited by prof.* Regardless of the specification we adopt, the coefficient of *Belong to prof's research network* is statistically significant at the 1% confidence level. Moreover, the magnitude increases relative to the results we have shown for the entire sample, reported in Table 3. For instance, when we include supervisor and student-university fixed effects, as well as the *N times master's university is cited by prof* variable (column VIII), the coefficient is now 0.14, while with the entire sample, it was equal to 0.11. This is exactly what we would have expected, since we are restricting the sample to the category of students for which information asymmetries are more severe.

⟨ Insert Table 4 about here ⟩

Despite the fact that our results hold with supervisor and student-university fixed effects, as well as with our control for the relevance of student i's university to the research of supervisor j, still we might have omitted some time-variant characteristics of a supervisor that are correlated with the error term. Another possibility is that we have omitted some characteristics of the PhD applicant that we do not observe, but could have been detected by her supervisor. To address this problem, we estimate an IV regression model, which treats *Belong to prof's research network* as an endogenous variable. For each PhD student coming from a given university, we instrument *Belong to prof's research network* using the share of coauthors affiliated with that university, of a professor of the same affiliation as j, but in a department specialized in a discipline as distant as possible from that of j. To choose among professors who appear to have the same "discipline distance" from supervisor j, we apply the criterion that the professor we associate with j has to have the highest number of past affiliations in common with j. The identifying assumption is that the research network of a scientifically distant professor should be uncorrelated with unobservable characteristics of supervisor j, her laboratory, or the type of PhD applicants j interviews. However, the instrument should be correlated with the research network of j, and thus with our endogenous variable, via the past affiliations j and her match have in common.

The results are reported in Table 5. They are limited to the sample of students who had graduated from a different university than their current affiliation. We estimate a IV continuous model where the dependent variable is the natural logarithm of the count of a student's publications plus one. We include professor fixed effects and fixed effects for country in which the PhD students obtained their master's degree. We refrain from including student-university fixed effects because our instrument is time-invariant. Hence, if we were to include both the instrument and student-university fixed effects, the impact of the instrument on *Belong to prof's research network* would be entirely captured by the student-university fixed effects. However, we do control for the quality of a student's past affiliation by including our university quality measures: *Ranking of master's university, Ranking of master's university (by field),* and *Pubs stock of master's university (by field).* Additionally, we control for the relevance of a student's past affiliation for supervisor j's research by including the variable *N times master's university is cited by prof.* We do not cluster standard errors around supervisors as the resulting, estimated covariance matrix of moment conditions is not of full rank. As shown in the first column, the instrument is highly correlated with the variable *Belong to prof's research network.* Its coefficient is positive, as expected, and highly significant, with a t-value of 7. The IV estimates are presented in the second column. The coefficient of our indicator variable, *Belong to prof's research network,* remains significant, this time at the 5% confidence level. Its magnitude appears to be larger by 0.41 than the estimate we would have obtained with an OLS model. One possibility for this result is that our instrument is not orthogonal to having graduated from a university from which a supervisor draws her coauthors, but picks up a set of factors that might affect student productivity. Another possibility, though, is that the OLS estimations might have omitted factors that are negatively correlated with our variable of interest. Suppose, for a moment, that a professor derives some benefits from hiring students who come from her research network, other than the student's productivity. These benefits might be, for instance, the supervisor's visibility in that university or with researchers in that university. This is not unlikely, and the benefits just mentioned are often seen as the other facet of selecting employees from a network. Suppose, further, that these additional benefits are larger if a supervisor selects students from universities that are especially relevant for her research. In this case, a supervisor might be willing to accept students coming from her research network, even though they do not have the highest expected productivity, but for which the other benefits are highest. Hence, not controlling for these additional benefits, which are likely to be negatively correlated with the expected productivity of a student, might lead OLS results to under-estimate the impact on student productivity of being affiliated with a university from which a supervisor draws her coauthors. Finally, an alternative explanation for our results is that our *Belong to prof's research network* variable is measured with error; thus, the increase in the coefficient is the result of a reduction in the standard attenuation bias present when variables are measured with error.

⟨ Insert Table 5 about here ⟩

4 Concluding Remarks

Are PhD students who are hired from a supervisor's network, on average, more productive? We examine this question using data on 4,666 PhD students who graduated at two major Swiss universities during 2000-2008.

We verify that PhD students who had obtained a master's degree at an institution from which a supervisor draws her coauthors are, on average, more productive. This result is robust across several model specifications, in which, for instance, we include supervisor fixed effects, measures for the quality of a student's university and for the relevance of the university to the supervisor's research. It is also economically important. Having restricted the sample to students who had obtained their master's at a university different from their current affiliation and having controlled for the relevance of a student's university to her supervisor's research, we find that the publication count is, on average, 16% higher for those students who had obtained their master's at a university with which their supervisors' coauthors are affiliated. The percentage increases to 21 if we adopt a more restrictive definition of student publications and consider in the publication count only those articles that had received a certain number of citations. When we estimate an instrumental variable model, we obtain a larger, and still significant coefficient for our variable of interest.

We note that our results are obtained in a European context, which, despite its heterogeneity under a number of aspects, comprises fairly culturally homogeneous countries. Thus, we expect that if we were to extend this analysis to a broader context, the effects of belonging to a supervisor's research network on student productivity would be substantially larger. In such a context, we might also observe that student-supervisor ethnic similarity or ethnic similarity between the student and the supervisor's PhD group is positively correlated with student productivity. Moreover, we could also observe that the effect of belonging to a supervisor's research network on student productivity is substantially larger than what we currently find, since membership to this network, in addition to easing problems of asymmetric information is also deemed to reduce communication costs between students and their supervisors (Hollingsworth and Fassinger, 2002; Ortiz-Walters and Gilson, 2005; Bozeman and Feeney, 2008; Blake-Beard et al., 2011). We believe that the value of this study is to show that even in fairly culturally homogeneous contexts such as ours, asymmetric information is a problem, and a problem that employers can overcome by choosing employees from networks to which they belong.

As a last note, while our results were derived from a sample of PhD students, and a sample of students affiliated with two elite European universities, they can easily be extended to any other setting, such as research centers in public or private institutions, in which the head of a research group is faced with the problem of screening potential, future members of a group.

Finally, a few caveats are in order. First, despite the fact that our results pass the test of an instrumental variable approach, and we select an instrument that is unlikely to be correlated with a supervisor's research, this instrument still does not have the same validity of an exogenous variation in the probability that a student has obtained her master's from one of the universities of her supervisor's coauthors. Second, due to limitations of our dataset, the results of our analysis are conditional on the PhD students being admitted in the doctoral program, and we cannot assess the impact network effects on the selection of these students. Extending the analysis to the role of supervisors' network effects on student selection remains a subject for future research.

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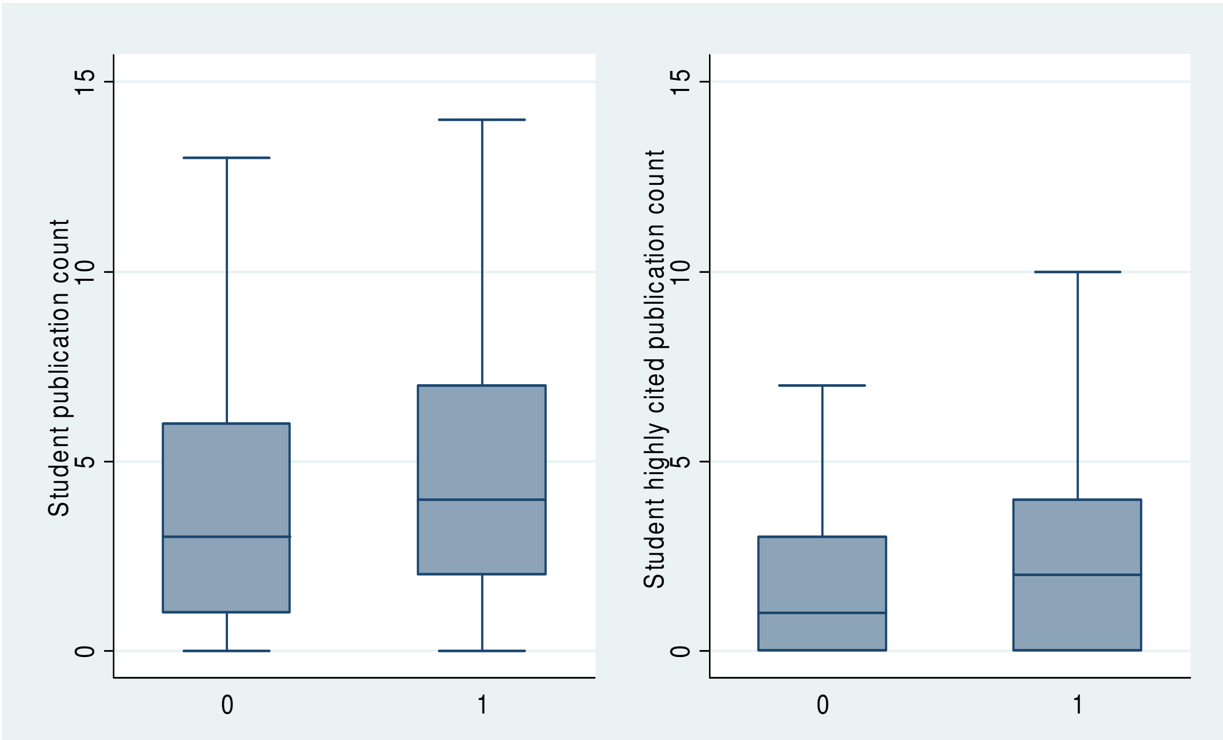
Figure 1: Box plots of student publications, distinguishing between students who do and do not belong to a supervisor's research network



Notes: For the student highly cited publication count, we count only those publications that had received a number of citations that is higher than a certain cutoff. The cutoff we use is the median number of citations that student articles (which were published in the same year and in the same field as that of the observed student's articles) had received. 1= a student had obtained her master's at one of the universities from which her supervisor draws her coauthors; 0= Otherwise.

Figure 2: Distribution of PhD students by their publication count

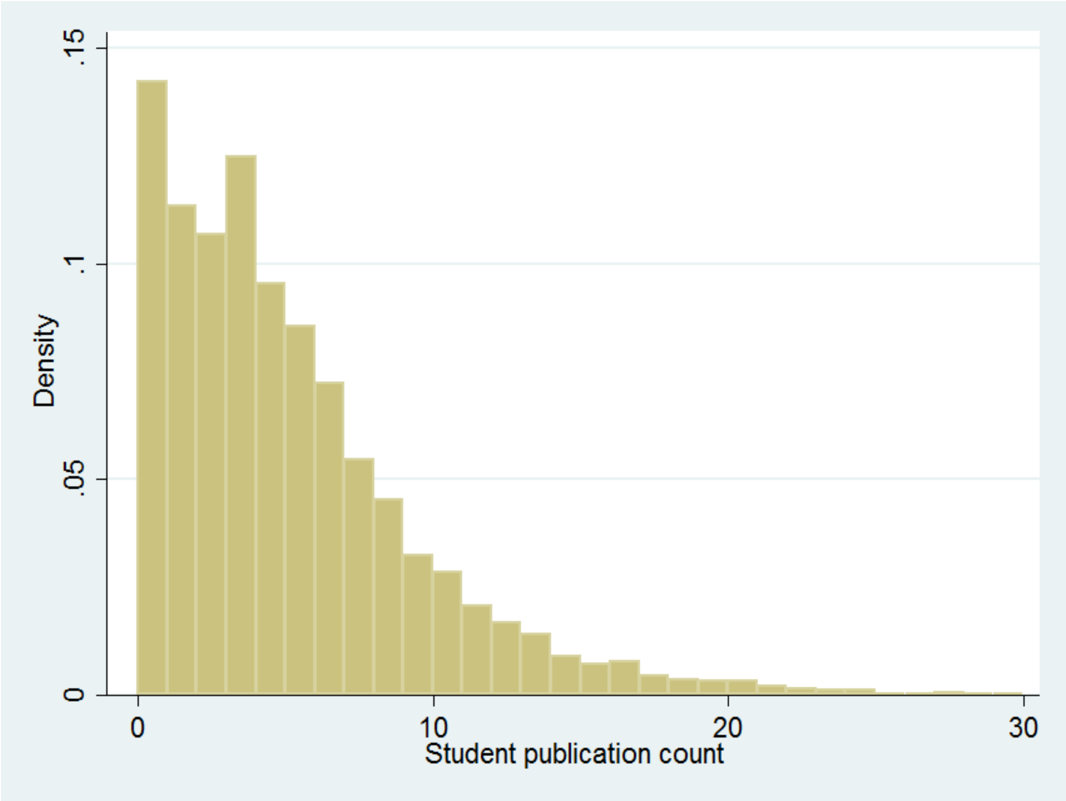


Table 2: Descriptive statistics

Variable	All students					Students who obtained their master's in a different university from their current affiliation				
	Obs.	Mean	Std.Dev.	Min	Max	Obs.	Mean	Std.Dev.	Min	Max
Graduate student publications	4666	4.69	4.38	0.00	30.00	2734	4.87	4.49	0.00	30.00
Graduate student highly cited publications	4666	2.46	2.77	0.00	20.00	2734	2.55	2.82	0.00	20.00
Belong to prof's research network	4666	0.68	0.47	0.00	1.00	2734	0.46	0.50	0.00	1.00
Pair-level controls										
Prof & PhD have same nationality	4666	0.30	0.46	0.00	1.00	2734	0.23	0.42	0.00	1.00
Prof & PhD come from same univ	4666	0.04	0.19	0.00	1.00	2734	0.04	0.20	0.00	1.00
% of Prof PhDs with same nationality as PhD i	4666	0.34	0.33	0.00	1.00	2734	0.21	0.29	0.00	1.00
N of institutions of a prof 's research network	4666	24.61	39.39	0.00	292.00	2734	4.31	12.47	0.00	155.00
Student Characteristics										
Student age	4666	26.56	2.51	21.00	40.00	2734	26.70	2.60	21.00	40.00
Gender	4666	0.23	0.42	0.00	1.00	2734	0.23	0.44	0.00	1.00
Master's at same univ as PhD	4666	0.41	0.49	0.00	1.00					
Pre-sample student pubs	4666	0.37	1.12	0.00	16.00	2734	0.42	1.28	0.00	16.00
Ranking of master's university	4666	194.51	217.13	1.00	601.00	2734	315.70	212.00	1.00	601.00
Ranking of master's university (by field)	4666	0.50	0.50	0.00	1.00	2734	0.15	0.36	0.00	1.00
Pubs stock of master's university (by field)	4666	7265.59	5655.29	0.00	40801.00	2734	4377.43	4367.98	0.00	40801.00
Professor-Lab Characteristics										
Prof age	4666	47.71	7.81	28.00	70.00	2734	47.54	7.73	29.00	70.00
Pre-sample prof pubs	4666	30.40	28.71	0.00	179.00	2734	31.59	28.64	0.00	179.00
Size PhD group	4666	7.00	6.00	0.00	41.00	2734	6.99	6.08	0.00	41.00
Grant amount	4666	74.34	90.22	0.00	1158.84	2734	78.14	85.76	0.00	1057.89
N of prof coauthors	4666	119.96	41.85	3.00	150.00	2734	122.48	40.54	3.00	150.00
N of institutions of a prof 's research network	4666	143.06	34.68	3.00	160.00	2734	144.38	33.40	3.00	160.00
Instrument and Placebos										
Research network instrument	4666	0.05	0.07	0.00	0.56	2734	0.01	0.03	0.00	0.56
Placebo most cited author	4666	0.62	0.48	0.00	1.00	2734	0.46	0.50	0.00	1.00
Placebo most similar author	4666	0.51	0.50	0.00	1.00	2734	0.36	0.48	0.00	1.00

Table 3: Regression results for the count of graduate student publications (*Sample= All students*)

Variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Belong to prof's research network	0.138***	0.102***	0.185***	0.122***	0.127**	0.089**	0.171***	0.110***
	(0.053)	(0.035)	(0.045)	(0.037)	(0.050)	(0.036)	(0.044)	(0.038)
Prof & PhD have same nationality	0.015	0.003	0.012	0.005	0.014	0.001	0.011	0.004
	(0.017)	(0.033)	(0.024)	(0.034)	(0.017)	(0.033)	(0.024)	(0.034)
Prof & PhD come from same univ	-0.086*	-0.040	-0.078	-0.041	-0.099*	-0.061	-0.089	-0.057
	(0.045)	(0.075)	(0.052)	(0.076)	(0.052)	(0.075)	(0.056)	(0.075)
% of Prof PhDs with same nationality as PhD i	0.079	0.063	0.084**	0.056	0.076	0.061	0.083**	0.055
	(0.049)	(0.053)	(0.037)	(0.055)	(0.048)	(0.054)	(0.036)	(0.055)
N times master's university is cited by prof					0.022***	0.029**	0.029***	0.028*
					(0.007)	(0.015)	(0.009)	(0.016)
Student age	-0.036***	-0.031***	-0.038***	-0.032***	-0.035***	-0.030***	-0.037***	-0.032***
	(0.003)	(0.006)	(0.006)	(0.007)	(0.003)	(0.006)	(0.006)	(0.007)
Gender	-0.222***	-0.208***	-0.228***	-0.199***	-0.221***	-0.208***	-0.227***	-0.200***
	(0.025)	(0.031)	(0.031)	(0.032)	(0.026)	(0.031)	(0.031)	(0.032)
Master's at same univ as PhD	0.017	-0.036	0.130***	0.126*	-0.019	-0.088	0.084***	0.079
	(0.041)	(0.056)	(0.013)	(0.076)	(0.043)	(0.065)	(0.023)	(0.082)
Pre-sample student pubs	0.073***	0.062***	0.100***	0.083***	0.074***	0.062***	0.101***	0.083***
	(0.013)	(0.014)	(0.010)	(0.013)	(0.013)	(0.013)	(0.010)	(0.013)
Ranking of master's university	0.000	0.000*			0.000	0.000**		
	(0.000)	(0.000)			(0.000)	(0.000)		
Ranking of master's university (by field)	0.068	0.103*	0.268	0.309**	0.061	0.093	0.271	0.306**
	(0.064)	(0.058)	(0.200)	(0.138)	(0.064)	(0.057)	(0.197)	(0.139)
Pubs stock of master's university (by field)	0.014	0.008	-0.064	-0.049	0.012	0.007	-0.069	-0.054
	(0.021)	(0.016)	(0.044)	(0.041)	(0.020)	(0.016)	(0.043)	(0.041)
Prof age	-0.007***	-0.337	-0.007***	-0.326	-0.007***	-0.338	-0.007***	-0.328
	(0.001)	(0.249)	(0.001)	(0.266)	(0.002)	(0.248)	(0.001)	(0.264)
Pre-sample prof pubs	0.005***	-0.004***	0.005***	-0.004***	0.005***	-0.004***	0.005***	-0.004***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Size PhD group	-0.004*	0.006	-0.004**	0.007	-0.004*	0.007	-0.004*	0.007
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Grant amount	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N of prof coauthors	0.116**		0.126**		0.110**		0.117*	
	(0.051)		(0.063)		(0.050)		(0.060)	
N of institutions of a prof 's research network	0.258***		0.236***		0.256***		0.233***	
	(0.063)		(0.088)		(0.064)		(0.086)	
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University-department FE	Yes		Yes		Yes		Yes	
University-nationality FE	Yes	Yes			Yes	Yes		
Student-university FE			Yes	Yes			Yes	Yes
Professor FE		Yes		Yes		Yes		Yes
Observations	4,650	4,621	4,372	4,278	4,650	4,621	4,372	4,278
# of Departments	19	19	19	19	19	19	19	19
# of University-Nationalities	53	53	48	46	53	53	48	46
# of Student-Universities	561	559	288	268	561	559	288	268
# of Professors	558	542	556	531	558	542	556	531
Log likelihood	-13367	-10369	-11543	-9219	-13362	-10363	-11535	-9215

Note: We estimate Poisson models. Robust standard errors in parentheses. * 0.10%, ** 0.05%, ***0.01%. Columns I and V present the baseline results with university-department dummies and dummies for the country in which a student had obtained her master's. Columns II and VI present the results with supervisor fixed effects. Columns III and VII present the results with fixed effects for the univiersities at which a student had obtained her master's. Finally, columns IV and VIII present the results with both supervisor and student-university fixed effects. The first four columns differ from the last four, as they do not include the *N times master's university is cited by prof* control.

Table 4: Regression results for the count of graduate student publications (*Sample= students who had obtained their master's at a different university from their current affiliation*)

Variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Belong to prof's research network	0.153***	0.132***	0.212***	0.164***	0.141**	0.110***	0.196***	0.139***
	(0.059)	(0.038)	(0.049)	(0.042)	(0.056)	(0.040)	(0.047)	(0.042)
Prof & PhD have same nationality	-0.005	0.012	-0.019	0.003	-0.007	0.004	-0.021	-0.003
	(0.021)	(0.049)	(0.046)	(0.055)	(0.021)	(0.048)	(0.047)	(0.055)
Prof & PhD come from same univ	-0.106	-0.013	-0.114	-0.026	-0.129*	-0.057	-0.145*	-0.082
	(0.072)	(0.085)	(0.080)	(0.088)	(0.076)	(0.087)	(0.084)	(0.089)
% of Prof PhDs with same nationality as PhD i	0.133*	0.060	0.124*	0.019	0.129*	0.060	0.119	0.021
	(0.074)	(0.086)	(0.074)	(0.090)	(0.074)	(0.087)	(0.074)	(0.090)
N times master's university is cited by prof					0.023**	0.046***	0.036*	0.057***
					(0.011)	(0.018)	(0.020)	(0.020)
Student age	-0.032***	-0.027***	-0.033***	-0.031***	-0.032***	-0.027***	-0.032***	-0.030***
	(0.006)	(0.008)	(0.009)	(0.010)	(0.006)	(0.008)	(0.009)	(0.010)
Gender	-0.220***	-0.228***	-0.229***	-0.219***	-0.220***	-0.228***	-0.228***	-0.217***
	(0.037)	(0.038)	(0.040)	(0.041)	(0.038)	(0.038)	(0.040)	(0.041)
Pre-sample student pubs	0.068***	0.070***	0.095***	0.085***	0.069***	0.070***	0.094***	0.085***
	(0.012)	(0.014)	(0.015)	(0.015)	(0.012)	(0.014)	(0.015)	(0.015)
Ranking of master's university	0.000	0.000**			0.000	0.000**		
	(0.000)	(0.000)			(0.000)	(0.000)		
Ranking of master's university (by field)	0.062	0.102*	0.233	0.339**	0.055	0.084	0.236	0.337**
	(0.069)	(0.062)	(0.210)	(0.154)	(0.070)	(0.060)	(0.206)	(0.155)
Pubs stock of master's university (by field)	0.023	0.008	-0.027	-0.028	0.021	0.005	-0.032	-0.037
	(0.021)	(0.018)	(0.050)	(0.047)	(0.021)	(0.018)	(0.049)	(0.047)
Prof age	-0.006**	0.031	-0.005**	-0.011	-0.006**	0.038	-0.005*	-0.005
	(0.003)	(0.365)	(0.003)	(0.383)	(0.003)	(0.376)	(0.003)	(0.382)
Pre-sample prof pubs	0.005***	-0.004***	0.005***	-0.005***	0.005***	-0.004***	0.004***	-0.004***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)
Size PhD group	-0.002	0.005	-0.003	0.006	-0.002	0.006	-0.003	0.007
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)
Grant amount	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
N of prof coauthors	0.066		0.084		0.061		0.075	
	(0.060)		(0.078)		(0.059)		(0.078)	
N of institutions of a prof 's research network	0.316***		0.276**		0.319***		0.282**	
	(0.083)		(0.110)		(0.082)		(0.110)	
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University-department FE	Yes		Yes		Yes		Yes	
University-nationality FE	Yes	Yes			Yes	Yes		
Student-university FE			Yes	Yes			Yes	Yes
Professor FE		Yes		Yes		Yes		Yes
Observations	2,718	2,601	2,440	2,266	2,718	2,601	2,440	2,266
# of Departments	19	19	19	19	19	19	19	19
# of University-Nationalities	53	53	48	46	53	53	48	46
# of Student-Universities	560	550	287	268	561	550	287	268
# of Professors	522	424	512	404	522	424	512	404
Log likelihood	-7782	-5592	-5974	-4481	-7779	-5583	-5969	-4473

Note: We estimate Poisson models. Robust standard errors in parentheses. * 0.10%, ** 0.05%, ***0.01%. Columns I and V present the baseline results with university-department dummies and dummies for the country in which a student had obtained her master's. Columns II and VI present the results with supervisor fixed effects. Columns III and VII present the results with fixed effects for the univiersities at which a student had obtained her master's. Finally, columns IV and VIII present the results with both supervisor and student-university fixed effects. The first four columns differ from the last four, as they do not include the *N times master's university is cited by prof* control.

Table 5: IV Regression results for the count of graduate student publications (*Sample=students who had obtained their master's at a different university from their current affiliation*)

Variable	**First-stage** (I)	**Second-Stage** (II)
Research network instrument	2.964***	
	(0.410)	
Belong to prof's research network		0.524**
		(0.244)
Prof & PhD have same nationality	0.076***	-0.041
	(0.026)	(0.049)
Prof & PhD come from same univ	0.177***	-0.130
	(0.053)	(0.104)
% of Prof PhDs with same nationality as PhD i	0.067	0.027
	(0.042)	(0.076)
N times master's university is cited by prof	0.093***	0.003
	(0.009)	(0.029)
Student age	-0.007*	-0.030***
	(0.004)	(0.007)
Gender	0.001	-0.172***
	(0.021)	(0.037)
Pre-sample student pubs	0.003	0.086***
	(0.007)	(0.012)
Ranking of master's university	-0.000	0.000***
	(0.000)	(0.000)
Ranking of master's university (by field)	0.061*	0.066
	(0.031)	(0.054)
Pubs stock of master's university (by field)	0.020**	0.014
	(0.009)	(0.017)
Prof age	0.175	0.122
	(0.232)	(0.411)
Pre-sample prof pubs	0.000	-0.004**
	(0.001)	(0.002)
Size PhD group	0.002	0.001
	(0.003)	(0.006)
Grant amount	-0.000	0.000
	(0.000)	(0.000)
Constant	-7.183	-2.997
	(9.533)	(16.869)
Year dummies	YES	YES
University-nationality FE	YES	YES
Professor FE	YES	YES
Observations	2,601	2,601
R-squared	0.318	
# of Professors	424	424

Note: For each PhD student coming from a given university, we use as an instrument the share of coauthors affiliated with that university, of a professor of the same affiliation as supervisor *j* but in a department specialized in a discipline as distant as possible from that of *j*. The professor we associate with *j* has to have the highest number of past affiliations in common with *j*. Standard errors are in parentheses. * 0.10%, ** 0.05%, ***0.01%.