Peer Effects in Academic Research: Senders and Receivers

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Abstract

Using an instrument based on a national contest in France determining researchers' location, we find evidence of peer effects in academia, when focusing on precise groups of senders (producing the spillovers) and receivers (benefiting from the spillovers), defined based on field of specialisation, gender and age. These peer effects are present even outside formal co-authorship relationships. Furthermore, the match between the characteristics of senders and receivers plays a critical role. In particular, men benefit a lot from peer effects provided by other men, while all other types of gender combinations produce spillovers twice as small. Part of the peer effects results from researchers switching research fields.

JEL codes: I23, J16, J24

Keywords: economics of science, peer effects, research productivity, gender publication gap

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1 Introduction

The production of academic knowledge seems to be organised so as to exploit peer effects: researchers are spatially clustered in academic departments and interact in conferences and seminars. In this process, peers may play a direct role as co-authors but they can also provide indirect benefits, by helping in the production/publication process, or by acting as role models. The design of academic institutions requires, however, a precise knowledge of both the size and nature of such peer effects but also the extent to which they could be heterogeneous across groups.

In this paper, exploiting a natural experiment that quasi-randomly allocates new peers to departments, we first provide causal evidence of the existence of peer effects. We show that peers provide indirect benefits over and above joint production through co-authorship. Furthermore, we show that these peer effects critically depend on the characteristics of both senders (those who produce the peer effects) and receivers (those who benefit from them). We show that the important senders are peers working in the same specific field of research (JEL code in our application) as receivers. Moreover, the match between the characteristics of senders and receivers plays a critical role, in particular their gender and age. Women benefit much less from peer effects provided by men, and younger researcher enjoy higher spillovers.

Our identification strategy uses the particular (and peculiar) promotion system from assistant to full professorship for economists in the public university system in France.[1] The recruitment procedure under study consists of a centralised contest to fill a number of positions opened in different universities. Candidates are ranked after a long examination spanning over a six-month period. Successful candidates, those ranked high enough to get a position, then sequentially make their choice according to their ranking. Universities cannot at this stage refuse a candidate. We observe the full choice set together with the

[1] This system, restricted to a set of disciplines historically related to law and political science, was essentially abandoned in 2015 (after the end of our data) for economics.

chosen position of candidates. Our empirical analysis shows that the only significant factor determining choices of candidates is the geographic distance from the university of origin. In particular, the average quality of the university in one's field of specialisation does not seem to play any significant role. As a consequence, reverse causality due to endogenous location choices does not appear to be a major concern. We also mitigate the issue of non-random spatial sorting by the use of individual and department fixed effects. The particular organisation of this allocation procedure allows us to go further and design an even more stringent identification strategy. We can restrict attention to the arrival in an university of professors ranked among the last ten in the contest. Those have a choice set that is very much reduced (the last ten universities that have not been chosen by a better-ranked candidate). The idea is that the specialisation of the new professor who lands in the department, and hence her productivity in the field, creates a variation in peers' productivity which can be considered as good as random. Those arrivals are thus used as an instrument for peers' productivity in the field of the department in which they are allocated.

Using this identification strategy, we find no evidence of peer effects when defining the relevant peer group as the entire department. However, we show that, in a given JEL code and year, one more publication by other members of the department increases one's productivity by a substantial range of 0.3 to 0.6 publications. The set of relevant senders are thus peers in the same field of study. Furthermore we show that the characteristics of the receivers matter as well. We show that women receivers benefit less from spillovers and so do older researchers.

As highlighted above, peer effects could encompass both direct spillovers from peers co-authoring papers, or indirect spillovers (for instance scientific or administrative help, role models). We thus distinguish the effect on papers without any peers as co-authors from papers either single-authored or co-authored with at least one peer. The largest share of the peer effects is driven by an increase in co-authored publications without peers. This demonstrates that peers matter, not only as co-authors, but also as providers of "indirect" spillovers.

Our paper also provides novel evidence on the key role played by the characteristics of the senders and receivers of peer effects. We show that senior researchers provide larger spillovers, and those peer effects benefit mostly junior researchers, highlighting the importance of specific matches between senders and receivers. The important role of gender is maybe more surprising. Men benefit a lot from peer effects provided by men, while all other types of matches produce smaller spillovers. If male peers increase their average level of publication by 1 paper, men receivers increase their number of single-author-equivalent publications by 0.524, while the effect is about twice as small if the receiver is a woman. This is the main driver for the result that women on average receive lower peer effects.

Finally we show that the arrival of new peers does not only affect productivity overall but also induces movements in the fields of research. We show that these new peers typically seem to attract department members to their fields of research while simultaneously diverting them from their original fields. Accounting for these substitution effects, we show that the arrival of a new peer still increases the number of single-author-equivalent publications by 0.116 on average.

Borjas and Doran (2015) differentiate three dimensions along which peers can create spillovers, namely ideas, geographic and collaboration space. The authors illustrate these concepts in the empirical application they consider: When some Soviet mathematicians left for the US, those who remained lost peers "who were close to them in idea space (i.e., working on the same topics), other mathematicians lost peers who were close to them in geographic space (i.e., worked in the same university department), and still others lost peers who were close to them in collaboration space (i.e., they had been co-authors prior to the collapse)."[2]

Most of the literature in the economics of science has shown the existence of spillovers in the collaboration space. In particular, several papers (Azoulay et al., 2010; Oettl, 2012; Jaravel et al., 2018) exploit the unexpected deaths of scientists to estimate the causal effect

[2] Using a natural experiment driving the location of labs on the Jussieu campus of Paris, Catalini (2018) highlights that being in the same geographic space (labs co-location) increases the likelihood of collaboration.

on the productivity of their co-authors or collaborators. Azoulay et al. (2010) find a strong effect following the death of star scientists, while Oettl (2012) qualifies this result by showing that the effect is restricted to helpful scientists (i.e. those acknowledged in several papers per year). Jaravel et al. (2018), using patent data, show that the effect is not restricted to the stars. Borjas and Doran (2015), after introducing the terminology, show evidence of spillovers in the collaboration space, but no evidence of peer effects in the geographical space, i.e. peers located in the same university and not directly collaborating.

The literature generally finds much weaker evidence for spillovers in the geographical space. Waldinger (2012) shows that the scientists whose departments suffered losses during the period from 1925 to 1938 did not publish less or worse compared to other scientists. Similarly, Borjas and Doran (2012) show a negative effect of the influx of Soviet Union mathematicians on the productivity of American mathematicians, due to competition for scarce resources, but no effect on overall productivity.[3] Similarly, Jaravel et al. (2018), using the death of scientists, show no effect on co-workers who are not collaborators and no effect on second degree connections.[4] Agrawal et al. (2017) highlight another channel through which geographical spillovers can occur. Exploiting the arrival of star scientists in evolutionary biology, they show that these researchers improve the productivity of the department. The main channel is that these initial arrivals increase the quality of future recruitments. In our context this mechanism is unlikely to be relevant since many of those who arrive through the contest do not stay more than 3 years and furthermore do not have the same attraction power as the stars in Agrawal et al. (2017).[5]

In our paper we show that, in order to find peer effects in the geographical space, one

[3]Without the use of natural experiments, a prior literature finds weak evidence of peer effects (Dubois et al., 2014; Kim et al., 2009). Waldinger (2010), using the same identification strategy based on the dismissal of Jewish professors in pre-war Germany, finds a negative effect on the career path of their PhD students.

[4]There is also a literature focusing on the role of the specific network structure. Ductor et al. (2014) show that incorporating detailed information on the co-author network improves the accuracy of predictions of future productivity. Head et al. (2019) show that ties such as having done the PhD in the same institution or sharing advisors matter for knowledge flows.

[5]In Agrawal et al. (2017) the stars are 6 times more productive than the rest of the sample while, in our context, the successful candidates are only 2.3 times more productive than the rest of the sample.

needs to restrict the set of relevant peers, in particular in terms of field of specialisation, age and gender. This effect is present even when we exclude collaborations (co-authored papers), and is thus not fully driven by spillovers in the collaboration space. We note several important differences in our setting, compared to most of the papers mentioned above. First, rather than observing the breaking-up of relations between peers (deaths or departures), we measure the effect of the arrival of new peers. Most importantly, a key focus of our paper is on the heterogeneity of spillovers based on characteristics of senders and receivers. To the best of our knowledge, heterogeneity in peer effects in academia has received little attention, except for heterogeneity in terms of field of research.

Gender-specific peer effects have been studied extensively in a connected literature on education. Results are somewhat mixed. Ficano (2012) shows, for college academic outcomes, that the peer effects are characterised by a strong own-gender pattern. In particular, male peers influence male students while females are unresponsive to either male or female average academic results, which echoes our results.[6] Regarding academic research, there is an extensive literature studying the productivity gap between men and women (West et al., 2013; Lariviere et al., 2018), with recent research showing that this could be partly driven by biases in the editorial process (Card et al., 2020; Hengel and Moon, 2020), but few contributions on peer effects by gender. Bostwick and Weinberg (2018) show that women that enter a PhD program in a year with more women are more likely to finish their PhD in time. In cohorts with particularly low fractions of female peers, women are substantially less likely to complete their PhD within 6 years than their male counterparts.

The remainder of the paper is structured as follows. We present our data on researchers' productivity and the institutional setup driving our supply shock of the spatial allocation of newly promoted economists in section 2. We present and discuss our identification strategy based on the national contest in section 3. Results are presented in section 4. Section 5

[6]Foster (2006) on the contrary finds little evidence of peer effects even when separated by gender. Hoxby (2000) finds some evidence of gender-based peer effects. In particular both males and females are found to perform better in classrooms with more females. In the same vein, Lavy and Schlosser (2011) find that an increase in the proportion of girls improves boys and girls cognitive outcomes.

concludes.

2 Data and institutional setting

2.1 Institutional setting

In the French public university system, which represents the vast majority of higher education, the hiring and promotion of professors follows a very codified and centralised process. Recruitments at the assistant professor level (called Maître de conférences) are decided by each university.[7] Maître de conférences is a civil servant position, hence tenured, but most academics aspire to promotion to the rank of Professeur des universités, equivalent to full professor, which involves a different salary path and increased recognition.

For a number of disciplines, including economics, the promotion to become Professeur des universités is done by means of a national contest, called concours national d'agrégation.[8] Over our sample period, the agrégation was biannual and entailed four steps over, approximately, a 6-month period, including a research seminar and three oral examinations. The jury then established a ranking of a number of candidates corresponding to the number of positions opened. At the end of the contest, candidates chose sequentially their university according to their final ranking. Importantly, the university chosen by candidates could not turn them down. Candidates lower in the ranking could only choose university position not chosen yet by a better-ranked candidate. When promoted, individuals were required to stay at least three years in the university they chose. After three years, professors were allowed to move to another university wishing to recruit them.

Several features of this system are useful for our study. First, it implies that we observe exactly the choice set of individuals and their chosen option, which allows us to study the

[7] Apart from rare exceptions, the characteristics of the position, in terms of teaching and administrative load as well as in terms of salary, are set centrally.

[8] Bosquet et al. (2019) provide a complete description of the system. It was abandoned for economics in 2015. Since then, candidates are simply "qualified" by a national committee, which means their name is put on a list for four years, from which universities can recruit.

determinants of their choices. Second, the conditions attached to each position, in particular teaching load or wages are centrally determined according to a well-defined grid. Some universities may be more accommodating in how to organise teaching, but the deviations from the standard conditions are small. This implies that we can control for most of the characteristics of the choices. Finally, the organisation of the contest implies that candidates ending up low in the ranking have a restricted choice set. This is a useful feature, which limits the possibility to sort on characteristics linked to productivity and that we exploit for identification.

2.2 Data and descriptive statistics

Our data uses the entire population of French academic economists provided by the French Ministry of Higher Education and Research and by the Centre National de la Recherche Scientifique (CNRS)[9] for the years 1990-2007. It includes information about the age, occupation and department membership at the individual/year level. Only individuals that are in departments larger than 4 full-time equivalent academics are kept, in order to restrict analysis to actual economics departments. We run regressions at the department level even when referring to a 'university' by slight abuse of terminology.[10] The Ministry dataset is completed by data on the outcome of nine agrégation contests taking place over our sample period, including the final ranking established by the jury.

We merge this data with the publications recorded in EconLit, the reference tool of the American Economic Association, for years 1991 to 2008, which includes the JEL codes of each publication. We measure the publication output of academics in field f at date t as the number of their publications in field f over a period τ. In our benchmark regressions,

[9]Not all academic economists hold a university position in French. There is a separate system involving full-time researchers. Most prominent among those are the researchers employed by the Centre National de la Recherche Scientifique (CNRS). CNRS researchers, who have their own hiring and promotion rules (also national), are hosted by academic departments within university and will thus be part of our sample. In particular these researchers can also benefit from the arrival of a university professor in the department.

[10]A few academics are affiliated to more than one university, in which case their output is split across their various universities when calculating the average outputs of the peers, and one individual observation for each department of theirs is considered in the estimations, and weighted accordingly.

τ corresponds to years $t+1$, $t+2$, and $t+3$. Calculating output as a moving average over three years is intended to account for the fact that scientific production is delayed by the publication process. Our measure follows recent work by Ductor et al. (2014), and assumes that knowledge produced in t will only be visible as published articles in the next three years (Waldinger, 2012, uses a one year lag because of shorter delays in the fields of chemistry, physics and maths that he studies). We present robustness checks for our main results varying the definition of τ in Appendix A.2.2. In line with common practice in the literature, each publication is weighted by the inverse of its number of authors. When measured at the field level, as in most of our estimations, $1/J$ of each publication is attributed to each of the J JEL codes (aggregated in 18 different categories at the letter level) mentioned in the publication.

Our final data includes 4,209 researchers working in 89 different departments.[11] Over our sample period, we use 7 contests to construct the instrument (see section 3), with the number of open positions per contest ranging from 15 to 33. Overall, 193 participants were promoted to the rank of full professor through these contests.

In Appendix Table A1, we compare the average annual publication records over our observation period of the different subgroups of interest for the rest of our analysis. Panel A first compares women and men. Women are less likely to publish than men and are less productive for all publication types except for co-authored publications involving at least one woman peer. The publication gap is large, with men publishing nearly twice as much as women. Senior researchers (above the median age of 45) publish less than junior researchers, the difference being particularly striking for co-authored publications.

Panel B of Table A1 compares the successful candidates in the contest to the rest of the population (left part of the panel). Successful candidates publish close to three times more than the rest of researchers we observe. Regardless of the type of publication under consideration (single authored or co-authored papers), successful candidates are more pro-

[11] The number of departments has been growing over our sample period, either because of creation of new universities or because departments grew larger than our minimal criterion of 4 researchers. The sample of researchers is not balanced, in part due to these inclusions over time.

ductive. Moreover, the right part of Panel B shows that those ranked among the last ten in the contest (column 5) are significantly less productive than those ranked above them (column 6), a reassuring feature for the quality of these promotion campaigns.

3 Identification

A standard specification to measure the effect of the number of peers and average peer quality on productivity is the following:[12]

$$y_{it} = \mu\, N_{u(i,t)t} + \beta\, Y_{u(i,t)t} + \theta_i + \gamma_{u(i,t)} + \alpha_t + \epsilon_{it}, \tag{1}$$

where y_{it} is the output (the productivity defined as the three year moving average of publications described above but aggregated over all JEL codes) of individual i working in university $u(i,t)$ at date t; θ_i, $\gamma_{u(i,t)}$ and α_t are individual, university and time fixed effects, respectively. $N_{u(i,t)t}$ is the number of peers at date t (i.e., the department size minus one). Finally $Y_{u(i,t)t}$ is the average output of the peers present in department $u(i,t)$ at date t using their average number of publications per year over the whole observation period, formally:

$$Y_{u(i,t)t} = \frac{1}{N_{u(i,t)t}} \sum_{\substack{j \in u(i,t) \\ j \neq i}} \frac{1}{T(j)} \sum_{t'=\underline{t}(j)}^{\bar{t}(j)} y_{jt'}, \tag{2}$$

where $\underline{t}(j)$ is the minimum between the first year when the individual appears in our panel and the date of their first publication minus three years (i.e. our best guess of the beginning of their career) and $\bar{t}(j)$ is the maximum between the last date they appear in our panel and their last publication minus three years (to assess the end of their career). $T(j) = \bar{t}(j) - \underline{t}(j) + 1$ is the career length. The purpose of considering the whole production of an individual is to restrict the variation of the peer effect variable over time, to be entirely driven by the composition of the department as in Waldinger (2012). We examine in section 4.2 the

[12] See for example equation (1) in Waldinger (2012).

robustness of our main results when we define production of the peer as the total production up to $t-1$.

Controlling for individual and university fixed effects rules out a number of endogeneity issues that relate to the sorting of researchers according to their permanent characteristics, research skills in particular. We show in Appendix Table A2 that our results are even robust to including match-specific (department times researcher) fixed effects, which should further address this concern. However, the OLS estimation of equation (1) might be subject to an extra bias due to a time-varying endogenous sorting of researchers taking place at the date they move, not only on average over their life. In particular, productive scientists may choose currently strong departments, in their fields of interest when estimations are conducted at the JEL code level, leading us to overestimate peer effects when estimating equation (1). We therefore build an identification strategy that exploits the national contest described in section 2.1. We instrument the productivity of peers at date t by the productivity of successful candidates who join the department at date t through the contest and who were ranked among the last, to limit the set of choices that were available to them.

Specifically, for department $u(i,t)$ and year t, we instrument the average peers' productivity $Y_{u(i,t)t}$ by:

$$Y_{a(i)t} = \frac{1}{N^a_{u(i,t)t}} \sum_{j \in \mathcal{A}_{u(i,t)t}} \frac{1}{T(j)} \sum_{t'=\underline{t}(j)}^{\bar{t}(j)} y_{jt'} \tag{3}$$

where $\mathcal{A}_{u(i,t)t}$ is the set of successful candidates who were ranked among the last ten in the contest and who arrived in university $u(i,t)$ at date t (if t even) or $t-1$ (if t odd) (the contest occurs every other year). $N^a_{u(i,t)t}$ is the cardinality of $\mathcal{A}_{u(i,t)t}$. Since all our specifications include department fixed-effects, the instrument is equivalent to the quality of the arriving peer compared to the department's average quality. Note that arriving candidates are actually better than the departments they join.

A key identifying assumption is that the candidates do not take into account the projected trend in productivity of the department (specific to their JEL codes when estimations are performed at the JEL code level) when choosing their location. While we cannot formally prove that this assumption is satisfied in the data, we show evidence consistent with this assumption. First, as described above, we restrict ourselves when constructing the instrument to the candidates ranked among the last ten in the contest. These candidates face a largely restricted choice set, and can be considered to arrive in the university quasi-randomly.[13]

Second, we show that among the factors that determine the location choice of researchers that passed the contest successfully, the main driver is distance to the university where the researcher held her previous position, and not at all the scientific quality of the university under consideration. In Table 1 we estimate a conditional logit model where the choice set for each participant in the contest is the actual choice set she faced, given her ranking and the choice of those ranked above her.[14] In column (1) we explain the location choice by the number of academics in the university and their average output, where the output in each field is weighted by the candidate's share of publication in that field. Candidates appear to marginally prefer universities with more peers and of higher average output. However, when we control in column (2) for the distance of the university under consideration with the university where the mover had her previous position, the scientific characteristics of the university no longer matter. Distance also clearly has the largest explanatory power. The results of Table 1 thus show that the productivity of members of the department in the main fields of interest of the candidate is not a key determinant of her choice. While it does not prove that future trends are not taken into account, it is reassuring evidence. This special role of distance is also present for candidates ranked among the last ten as shown in columns (3) and (4) of Table 1.

The last concern is related to the specific structure of the contest. Since universities do not open a position at each contest, there might be an incentive for a particular candidate

[13] We provide robustness checks in section 4.2 using all successful candidates except those ranked among the first 10.

[14] For the columns with only the last ten ranked (columns 3 and 4), building on those 9 contests, there are therefore $9 \times 54 = 486$ potential observations. In reality, some universities offered several jobs, and the actual number of observations drops to 406.

Table 1: Location choices

	All successful cand.		Last ten only	
	(1)	(2)	(3)	(4)
Log number of academics	0.121	0.001	1.681	3.277
	(0.818)	(0.870)	(3.039)	(3.456)
Average academics' output	6.608^a	3.577	10.237^c	-2.184
	(1.947)	(2.257)	(5.233)	(5.370)
Dummy staying in previous university		-2.537^a		-4.496
		(0.960)		(3.220)
Log distance previous university		-1.158^a		-1.897^a
		(0.158)		(0.539)
Pseudo-R^2	0.16	0.35	0.39	0.57
Observations	2,814	2,814	406	406

Notes: Conditional logit estimated. All regressions include department fixed effects. Standard errors between parentheses. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively. Average academics' output: Average sum of publications of academics (discounted by publications' age with a logistic function), weighted by the JEL specialisation of successful candidates: $\sum_{f=1}^{18} \frac{\tilde{Y}_{uft}}{N_{ut}} \frac{\tilde{y}_{ift}}{\tilde{y}_{it}}$ with $\tilde{y}_{it} = \sum_{t'} \frac{1-\exp(-10/(t'+1)^{1.8})}{1+\exp(-20/(t'+1)^{1.8})} y_{it'}$.

and a given university to agree on the timing of application and opening. This appears unlikely, since the strategy is risky: the candidates control neither their ranking nor the choices of those ranked above them, so it might be difficult to collude effectively. This is particularly true for the low ranked candidates and thus our strategy of restricting ourselves to the last ten candidates should alleviate this concern. We nevertheless present in Table 2 a conditional logit estimation where the dependent variable is the chosen contest (by each candidate) regressed on average characteristics of the universities opening a position in that year.[15] We find that none of the characteristics of the contest, except for the number of positions opened in that particular year, can explain why a candidate applied in that year. In particular, neither the distance nor the quality of the universities appear to play a role, strongly suggesting that the strategic choice of when to apply is not an issue.

Most of our estimations will use a modified version of equation (1) in order to conduct

[15] Specifically, for an individual applying in contest t we explain the choice between contest t and contests $t-1$ and $t+1$ based on average characteristics of each contest. We thus implicitly assume that the candidate could apply in $t-1$, which was not necessarily the case.

Table 2: Contest choice of successful candidates

	(1)	(2)	(3)	(4)	(5)
Number of jobs	0.069^a				0.113^a
	(0.023)				(0.039)
Average dept. size		-0.014			0.018
		(0.011)			(0.015)
Average academics' output			-2.938		9.919
			(7.798)		(9.381)
Average distance				0.001	-0.001
				(0.001)	(0.001)
Pseudo-R^2	0.03	0.01	0.00	0.01	0.04
Observations	423	423	423	423	423

Notes: Conditional logit estimated. Observations are at the individual-contest level, where for an individual recruited in contest t we use contest t and contests $t-1$ and $t+1$. The dependent variable takes the value 1 if the candidate was recruited in contest t. All explanatory variables are average characteristics of the universities opening positions in that contest. Standard errors between parentheses. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively. Av. academics' output: Average sum of publications of academics (discounted by publications' age with a logistic function), weighted by the JEL specialisation of successful candidates: $\sum_{f=1}^{18} \frac{\tilde{Y}_{uft}}{N_{ut}} \frac{\tilde{y}_{ift}}{\tilde{y}_{it}}$ with $\tilde{y}_{it} = \sum_{t'} \frac{1-\exp(-10/(t'+1)^{1.8})}{1+\exp(-20/(t'+1)^{1.8})} y_{it'}$.

the analysis at the field (JEL code) level. The main change is that each publication is first equally split between all its JEL codes. The new dependent variable is y_{ift}: an individual i's output at date t, defined at the JEL code level (f). Similarly, the peer effect variable is computed at the JEL code level, and denoted $Y_{u(i,t)ft}$. This yields specification (4):

$$y_{ift} = \mu\, N_{u(i,t)t} + \beta\, Y_{u(i,t)ft} + \theta_i + \gamma_{u(i,t)} + \alpha_{ft} + \epsilon_{ift} \tag{4}$$

In that case, the instrument is also similarly computed at the JEL code level. In most of our analysis, the estimation clusters the random component at the departement-JEL level. This is intended to capture the fact that errors for all members of a department in a given JEL code could be correlated even when controlling for department permanent characteristics with the department fixed effects, $\gamma_{u(i,t)}$.

Choosing the right level of clustering is a subtle issue as discussed in Abadie et al. (2017) and MacKinnon and Webb (2020). The literature argues that the number of clusters should be neither too high nor too low. Since we measure peer effects at the department-JEL level, and because the number of departments is not always large enough to cluster at the department level (only 19 departments in the IV regressions) and we include in any case department fixed effects, department-JEL is our preferred level of clustering. We show that our results are robust to alternative level of clustering. In our first main table of results, Table 3, we report three series of standard errors, with department, department-time, and department-JEL clustering. This is also done in appendix A.3 for the next four tables. Overall, standard errors are not critically affected. They are only slightly larger in the case of department clustering, which is not very surprising given the simultaneous consideration of department fixed effects and the small number of clusters in particular. But most of our main results remain significant even with that level of clustering as detailed below.

4 Results

4.1 Peer effects in academia

We start by estimating equation (1) with results presented in Table 3. In column (1), we observe that, when individual i's output is aggregated over all JEL codes and the peer group is defined as the entire pool of economists in the department, there is no evidence of peer effects.[16] This absence of any effect holds in column (2) where the dependent variable is measured at the researcher-JEL code-year level (one observation for each triplet) but keeping the peers' productivity variable at the aggregate level.

In column (3) we estimate equation (4) now with both the productivity of the individual y_{it} and of her peers $Y_{u(i,t)t}$ measured at the JEL code level, i.e. y_{ift} and $Y_{u(i,t)ft}$. In other words, we constrain the pool of senders and receivers to be working in the same field. We find that if other members of the department increase on average their productivity in a JEL code by 1 publication, a member of the department would publish 0.623 additional

[16] The number of peers variable is normalised by the average number of peers in the sample without any loss of generality.

publications in that JEL code. By contrast, the total number of peers, which could capture economies of scale at the department level, has no significant impact. The average peers' productivity in the JEL code is the key external factor influencing productivity.

In the appendix, we provide a number of robustness investigations to this first result, aimed at addressing two main concerns. First, when running the analysis at the JEL code level, the dependent variable often takes zero values. Second, the degree of specialisation of the university in the JEL code could imply a specific effort to promote the field, which could be driving the effect, wrongly attributed to peers' productivity in the JEL code. Table A3 in Appendix A.2.1 shows that our results regarding the impact of peer productivity in the same field are robust to the removal of individuals who never publish in general, or never publish in a particular JEL code, and to the inclusion of the share of peers publishing in the JEL code.[17] If anything, those robustness tests increase the magnitude of the peer effect.

Columns (1) to (3) in Table 3 show that the relevant group of senders is the set of peers working primarily in the same JEL code. We now examine the role played by the characteristics of the receivers, paving the way for our detailed analysis of this question in section 4.3. In column (4) we show that women receivers benefit less from peer effects than men and column (5) shows that older researchers benefit less than younger ones. Comparing a woman to a man or a researcher to a researcher 15 year older divides the magnitude of the peer effect by around two. Note however that on average women publish 0.188 papers for every 0.326 papers produced by men (see Table A1), also around half, so that in proportional terms, or 'per paper published', these peer effects are approximately of the same size for men and women.

As explained in section 3, in order to address the endogeneity of the productivity of the peers, we use an IV strategy based on the instrument defined in equation (3). Results are presented in Table 4. For each specification, we also present the OLS results when

[17] Bosquet and Combes (2017) do not find any impact of department size on publications either but a role of the share of peers publishing in the JEL code.

Table 3: Peer effects, OLS estimations

	(1)	(2)	(3)	(4)	(5)	(6)
	Tot.	JEL	JEL	JEL	JEL	JEL
Number of peers	0.092	0.000	0.000	0.000	0.001	0.001
	[0.090]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
	{0.047}^{c}	{0.000}	{0.001}	{0.001}	{0.000}	{0.000}^{b}
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Av. output of the peers	0.055	-0.001				
	[0.581]	[0.004]				
	{0.265}	{0.002}				
		(0.003)				
Av. output of the peers in JEL			0.623	0.693	0.607	0.697
			[0.038]^a	[0.039]^a	[0.034]^a	[0.035]^a
			{0.016}^{a}	{0.017}^{a}	{0.014}^{a}	{0.016}^{a}
			(0.035)^a	(0.035)^a	(0.030)^a	(0.030)^a
– × Woman				-0.316		-0.418
				[0.054]^a		[0.048]^a
				{0.022}^{a}		{0.022}^{a}
				(0.050)^a		(0.045)^a
– × Age					-0.022	-0.025
					[0.003]^a	[0.003]^a
					{0.001}^{a}	{0.002}^{a}
					(0.003)^a	(0.003)^a
R^2	0.41	0.09	0.12	0.12	0.12	0.12
Observations	42,521	771,498	771,498	771,498	771,498	771,498

Notes: The dependent variable measures individual output, specifically 3-year moving average of the number of articles divided by their number of authors, and is measured at the JEL-code level from column (2). All regressions include age, individual and department fixed effects. Column (1) also include year fixed effects and columns (2) to (6) year-JEL fixed effects. For explanatory variables, the number of peers is divided by its sample mean (67.6). "Av. output of the peers'" is defined in equation (2) and is measure at the JEL-code level from column (3). Age is centered with respect to the sample mean when interacted. Standard errors clustered by department between brackets, department-year between braces and department-JEL between parentheses. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively.

restricting the sample to the observations used in the IV regression.[18] The instrument is not weak with a Kleibergen-Paap statistics well above the threshold values for a maximal size of 10% provided by Stock and Yogo (2005) (Table 5.2), equal to 16.38 for column (2) and to 7.03 for columns (4) and (6). First-stage estimations presented in Appendix Table A23 confirm the high-explanatory power of the instruments that furthermore always have a significant

[18]Note that the OLS results on this restricted sample suggest lower peer effects than in Table 3 and therefore stronger peer effects for better universities. Indeed our IV strategy tend to unbalance the panel towards universities of lower quality as better ones either do not open positions at the agrégation, since they cannot fully chose the candidates, or if they do, receive better ranked candidates.

impact with the expected sign on the instrumented variables. Column (2) confirms the result that average productivity of the peers in a JEL code increases the productivity in that field. The IV coefficient is smaller than the OLS one (around 20% smaller), confirming a positive bias in OLS estimates. IV estimates suggest that if members of the department increase on average their JEL code productivity by 1 publication, a member of the department would publish approximatively 0.3 additional publications in that JEL code.

Table 4: Peer effects, IV estimations

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.003^b	0.002^c	0.003^b	0.002^c	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Peers' productivity	0.385^a	0.306^b	0.418^a	0.414^a	0.341^a	0.316^b
	(0.053)	(0.122)	(0.051)	(0.139)	(0.049)	(0.123)
$-\times$ Woman			-0.140^b	-0.515^a		
			(0.065)	(0.169)		
$-\times$ Age					-0.030^a	-0.026^a
					(0.003)	(0.008)
R^2	0.10		0.10		0.10	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		28.1		14.0		15.2

Notes: The dependent variable measures individual output, specifically 3-year moving average of the number of articles published in the JEL code divided by their number of authors. All regressions include age, individual, department and year-JEL fixed effects. For explanatory variables, the number of peers is divided by its sample mean (67.6). "Av. output of the peers" is defined in equation (2) and is measure at the JEL-code level. Age is centered with respect to the sample mean when interacted. Instrumented variables are the average output of the peers in column (2) and interaction terms with women or age in columns (4) and (6). The instrument is the average successful candidates' productivity defined in equation (3) at the JEL-code level in column (2) and its interaction with women and age in columns (4) and (6). First stages are reported in Appendix Table A23. Standard errors clustered by department-JEL between parentheses. Standard errors clustered by department and by department-year are provided in Appendix Table A17. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively.

In columns (3) to (6) of Table 4, we confirm that gender and age affect the capacity to benefit from spillovers. The interaction between age or gender and average peers' productivity is instrumented by the interaction of age or gender and the instrument for peers' productivity. As regards the role of gender, our results suggest that in fact women do not benefit at all from peer effects. This is confirmed in Appendix Table A8, where we estimate peer effects separately for men and women. While men significantly benefit from peers, the coefficient for women is not significantly different from zero when instrumenting average peers' productivity. The impact of age is similar to the one obtained with OLS.

Our instrumentation strategy has the flavour of a difference-in-difference approach for which we could plot difference in outcomes between treated (receiving a successful candidate) and non-treated departments to visually assess the impact of the treatment and the absence of different pre-trends. This is not that obvious to do, however, since our treatment is continuous, departments are treated at different dates, and some of them are treated many times. Still, on the sample corresponding to IV estimations, we run a regression with our individual controls and department-JEL-time fixed effects. We then regress these fixed-effects on the department and JEL-time fixed effects that are also controlled for in our estimations and we then back up the residuals. For each contest, we group the university-JEL cells among those that do receive at least a successful candidate in the JEL code, and those that do not. Finally, we average these residuals separately for the two groups and over all contests, weighting by the number of their individual-JEL observations for the corresponding year. Figure A1 plots the dependent variable for the two groups before and after the arrival of a successful candidates, with 95% confidence intervals. Date 0 corresponds to the arrival of the successful candidate in the new university. There is no pre-trend for either group. We see the effect of the treatment in the period that follows the arrival. In Appendix Table A21, we also control for department-trends for Table 4 estimations on top of all other controls. Point estimates are very similar to those obtained without such trends and significance is unchanged.

As discussed in the introduction, Borjas and Doran (2015) differentiate peer effects along the geographical and the collaborative spaces. In the collaborative space, a researcher may increase productivity of her peers through co-authorship. In the geographical space, peers can provide indirect benefits, even in the absence of formal co-authorship, by assisting in the production/publication process. These benefits range from commenting the paper, suggesting the correct venues to present, putting researchers in contact with the relevant people in the profession[19] or acting as role models (setting the example in terms of research practices and create an environment that increases productivity).

In our setting, a newly arrived peer can create spillovers in both spaces. We now attempt to distinguish these two types of spillovers, by differentiating papers co-authored with peers from other papers. Specifically, for researcher i in university u ar date t, we define publications co-authored with peers as those written with at least one co-author who was affiliated to u, 1, 2 or 3 years prior to publication.

Results in Table 5 suggest that direct co-authorship is not the only channel for spillovers. Columns (3) and (4) show that there is an effect of the average productivity of peers on the number of publications co-authored with peers, but columns (5) and (6) also show that average productivity of peers affects co-authored papers without peers. According to the IV results, if peers publish an additional paper in a JEL code on average, this increases the number of co-authored papers without peers by 0.133. Thus, we find evidence of peer effects in the geographical space. When instrumenting, we do not find any significant effect of peers on solo-authored papers, suggesting that these indirect spillovers are likely not driven by peers acting as role models.[20]

4.2 Robustness checks

In this robustness section, we first show that our results are not driven by the fact that the instrument uses only the last ten candidates ranked. In Appendix Tables A9, and A10, we present results obtained when constructing the instrument with all successful candidates except the first ten (the ones that are the least constrained in their location choice). The main conclusions are unchanged.

We also consider a robustness check related to the way the productivity of peers is mea-

[19]There is also evidence that peers can help in their position as editors (see Colussi, 2018).

[20]Some papers suggest to use publication measures weighted by the quality of the journal. In Appendix A.2.3, Tables A13 and A14 reproduce Tables 4 and 5 considering the journal-quality adjusted publication measure used by Bosquet and Combes (2017). Conclusions are similar.

Table 5: Splitting production in three categories of papers

	Single-author publications		Co-authored publications			
			With peers		Without peers	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.002^b	0.001	0.001^c	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Peers' productivity	0.157^a	0.037	0.145^a	0.136^b	0.083^a	0.133^c
	(0.027)	(0.073)	(0.029)	(0.066)	(0.016)	(0.069)
R^2	0.07		0.08		0.09	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		28.1		28.1		28.1

Notes: The dependent variable measures individual output, specifically 3-year moving average of the number of articles published in the JEL code divided by their number of authors. To compute the dependent variable, we split the articles in three categories: in columns (1) and (2) we keep only single-authored papers, in columns (3) and (4), papers co-authored with peers and in columns (5) and (6), papers co-authored without peers. All regressions include age, individual, department and year-JEL fixed effects. For explanatory variables, the number of peers is divided by its sample mean (67.6). "Av. output of the peers" is defined in equation (2) and is measure at the JEL-code level. Age is centered with respect to the sample mean when interacted. Instrumented variable is the average output of the peers. The instrument is the average successful candidates' productivity defined in equation (3) at the JEL-code level. First stages are reported in Appendix Table A23. Standard errors clustered by department-JEL between parentheses. Standard errors clustered by department and by department-year are provided in Appendix Table A18. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively.

sured. In the previous section, all results were presented using the sum of papers produced by the peers over their lifetime to measure peer's productivity more accurately. The successful candidates in particular are still early in their career and their publication profile at the time when they arrive in their new position (just after the contest) might be a noisy measure of their true quality. Another advantage of that approach is to make the peer's quality constant over time and the changes in the peer variable only arise from the arrivals and departures occurring at a department. This choice however creates a potential issue since, if peers themselves benefit from spillovers, a reverse causality bias occurs. We therefore present in Appendix Table A11 the equivalent of Table 4 with productivity of peers and the instrument variables calculated using only production up to $t-1$. We see that even though the instrument is weaker, consistent with the idea that productivity is measured more imprecisely, the coefficients are of similar magnitude.

Finally in Table A15 and A16, we reproduce Tables 4 and 5, using an alternative instrument. Rather than instrumenting the productivity of peers by the productivity of the successful candidate ranked among the last 10 in the contest arriving in the department, we use the productivity of the contest participant whose department of origin is the closest to the department of interest. This instrument exploits the results on distance obtained in Table 1. The instrument is slightly weaker (as expected), but the results are again qualitatively similar.

4.3 The appropriate match between senders and receivers

Having established the existence of peer effects, we now examine in more depth their heterogeneity, and in particular how they depend on the characteristics of both senders and receivers. In the previous sections we have shown that peer effects are present when focusing on particular groups of senders, those publishing in the same field as the recipient, and for certain groups of receivers, such as young and male academics. In this section we explore whether the particular match between the sender and the receiver matters, focusing in particular on age and gender.[21] For instance, are men more likely to provide peer effects to other men?

To answer this type of question, we return to using OLS with individual, university and time fixed effects, since our identification strategy does not allow us to appropriately instrument for specific matches between senders and receivers. This is particularly true when studying the role of gender, given that substantially fewer women enter the contest.

Column (1) of Table 6 shows that male peers provide higher spillovers on average than female peers. If male peers' average number of publications in a JEL code is increased by 1 article, the production of any researcher increases by 0.464 in that JEL code. However this average effect hides differential impacts of the match. Column (2) interacts the variables with the gender of the individual receiving the peer effect. Men and women benefit in the

[21] There is a large literature in management on absorptive capacity (Cohen and Levinthal, 1990), i.e. the capacity to benefit from incoming spillovers, which varies substantially across firms.

same way from women peers but women benefit significantly less from male peers than men do. Overall, we find that peer effects are similar across all types of matches, except when men are matched with men, a match that produces significantly higher spillovers.

Table 6: Gender mechanisms, OLS

Publications	All		Single author	Co-auth. w/o. peers	Co-authored with peers		
					All	1+ wom.	only men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of peers	-0.000	-0.000	-0.001	0.000	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Peer % women	0.003[c]	0.003[c]	0.001	0.001	0.001[b]	0.001[b]	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Male peers' prod.	0.464[a]	0.524[a]	0.230[a]	0.184[a]	0.110[a]	0.008[a]	0.102[a]
	(0.040)	(0.044)	(0.030)	(0.014)	(0.013)	(0.003)	(0.012)
– × Woman		-0.276[a]	-0.143[a]	-0.088[a]	-0.046[a]	-0.003	-0.043[a]
		(0.054)	(0.034)	(0.021)	(0.012)	(0.004)	(0.011)
Fem. peers' prod.	0.174[a]	0.182[a]	0.053[b]	0.072[a]	0.057[a]	0.034[a]	0.023[b]
	(0.027)	(0.029)	(0.022)	(0.011)	(0.015)	(0.007)	(0.010)
– × Woman		-0.026	-0.012	-0.020	0.006	0.002	0.004
		(0.052)	(0.031)	(0.021)	(0.013)	(0.008)	(0.011)
R^2	0.12	0.12	0.07	0.11	0.08	0.06	0.07
Observations	771,498	771,498	771,498	771,498	771,498	771,498	771,498

Notes: The dependent variable measures individual output, specifically 3-year moving average of the number of articles published in the JEL code divided by their number of authors. Column (6) compute thiss individual output based on publications co-authored with peers among whom there is at least one woman and column (7) when all peer co-authors are men. All regressions include age, individual, department and year-JEL fixed effects. For explanatory variables, the number of peers is divided by its sample mean (67.6). "Male and fem. peers' prod." defined as: Average number of publications per year (in the field) of male and female peers, respectively. Standard errors clustered by department-JEL between parentheses. Standard errors clustered by department and by department-year are provided in Appendix Table A19. [a], [b], [c] indicate significance at the 1%, 5% and 10% level, respectively.

We then break down the effect according to the type of publication, in the spirit of the previous section. Regardless of publication type, the match between male senders and male receivers stands out as the most productive. For instance, column (3) shows that if male peers increase their average level of publication by 1 paper, men receivers increase their number of single-author publications by 0.230, while the effect is about twice as small if the receiver is a woman. The only exception regards publications co-authored with at least one woman peer (column 6). In this case, the identity of the receiver does not matter. On the contrary, if all peers are male on a publication involving only men co-authors, men benefit again twice more than women from peer effects (column 7). It is useful to keep in perspective that according to the descriptive statistics, women produce almost half what men produce on average in our sample. Thus in proportional terms, women benefit to a similar extent as men from male peers, but benefit twice as much from peer effects coming from female peers.

Table 3 had also highlighted the role of age in peer effects. We now explore whether match specificities also matter in the case of age. Distinguishing between junior researchers and senior researchers (above and below the median age at 45), we show in Appendix Table A22 column (1) that senior researchers provide higher levels of peer effects than younger ones. However, senior researchers benefit less from spillovers, and this is particularly true when the spillovers are provided by junior researchers, a rather intuitive result. Once again, these results highlight the particular importance of the characteristics of the match between senders and receivers.

4.4 Peer effects and substitutions across fields

In this last section, we assess whether a change in the composition of academic peers can trigger changes in the research agenda of their colleagues – on top of the different direct and indirect channels of increased productivity studied in the above sections. A likely mechanism is that the arrival of a particularly productive researcher in one JEL code can attract other researchers to produce research in that same JEL code. This could be either new research or a reallocation of efforts and time away from the original field. Both the new production and the possible diversion/substitution effects are interesting, and we explore these in Table 7. The organisation of this table follows the same logic as the four last columns of Table 3, and adds peers productivity in other fields as an additional explanatory variable.

We find in column (1) that increasing the productivity of peers in a different field than the JEL code under consideration reduces output in that JEL code by 0.029 publications. This statistically significant coefficient clearly indicates a substitution effect. Moreover, columns (2) to (4) show that the effect of gender and age is consistent with what we previously found: the substitution effect is weaker for women and older researchers who benefit less from peer effects.

Table 7: Peer effects and movements across fields, OLS

	(1)	(2)	(3)	(4)
Number of peers	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Av. output of the peers in JEL	0.607^a	0.679^a	0.589^a	0.682^a
	(0.033)	(0.032)	(0.027)	(0.027)
$-\times$ Woman		-0.327^a		-0.432^a
		(0.051)		(0.046)
$-\times$ Age			-0.021^a	-0.024^a
			(0.003)	(0.003)
Av. output of the peers in other fields	-0.029^a	-0.032^a	-0.027^a	-0.032^a
	(0.004)	(0.004)	(0.004)	(0.004)
$-\times$ Woman		0.017^a		0.022^a
		(0.004)		(0.004)
$-\times$ Age			0.001^a	0.001^a
			(0.000)	(0.000)
R^2	0.12	0.12	0.12	0.12
Observations	771,498	771,498	771,498	771,498

Notes: The dependent variable measures individual output, specifically 3-year moving average of the number of articles published in the JEL code divided by their number of authors. All regressions include age, individual, department and year-JEL fixed effects. The number of peers is divided by its sample mean (67.6). "Av. output of the peers" is defined in equation (2) and is measure at the JEL-code level. Age is centered with respect to the sample mean when interacted. Standard errors clustered by department-JEL between parentheses. Standard errors clustered by department and by department-year are provided in Appendix Table A20. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively.

What do those results imply for the overall impact of the arrival of a peer? Given that there are 18 JEL codes overall, the arrival of a productive researcher in a given JEL code reduces productivity in the rest by $17 \times 0.029 = 0.490$ which has to be compared to the 0.607 additional publications in the JEL code under consideration (column 1). Accounting for the substitution effects, an overall publication gain remains, at 0.116, which is significantly positive given estimated standard-errors (p-values of 0.118, 0.002 and 0.033 with department, department-time and department-JEL clustering, respectively). Doing the same calculation by gender using the results of column (2), the overall gain remains 0.130 (p-values of 0.096, 0.001 and 0.022) for men but is weaker for women (0.086) and insignificant (p-values of 0.249, 0.031 and 0.179).

The balance is thus positive but much smaller. This can partially explain why peer effects appear to be low when in column (1) of Table 3 we do not zoom in at the JEL-code level. Beyond these average substitution effects across fields, some stronger substitution effects could emerge between more closely related fields. Studying JEL pairwise-specific peer effects, possibly differentiated by type of senders or receivers, could be the object of interesting future work.

5 Conclusion

This article shows that peer effects in academia are present and large within precisely defined fields and for some groups of researchers, based on their gender and age. We find that another important component of peer effects is the match between receivers and senders. Moreover, these spillovers are not purely driven by co-authorship, but indirect spillovers also seem to matter. An important finding is that women benefit much less from positive spillovers brought by the arrival of new male researchers in their department. Conversely, men and women benefit equally from peer effects generated by female economists, which are, however, less strong.

Our results have policy implications for the organisation of academia. First, they highlight the value of specialisation and the importance of gender and age composition of the department, as channels to facilitate spillovers. Second, they speak to the important publication and promotion gaps between women and men observed in academia (see Bosquet et al., 2019). The fact that women benefit less from peer effects produced by men, can explain part of the publication gap between men and women (see West et al., 2013; Lariviere et al., 2018), which we also find in our data. What is the source of these gender-specific effects? Is it that male peers are less available to comment on female colleagues' work or help them advance their career, or even prejudiced to do that? Or is it that women researchers are more reluctant to approach male colleagues to benefit from incoming spillovers? Unfortunately, our data does not allow us to distinguish between these alternative mechanisms. But we view those questions as important themes for future research, in order to setup policies to correct for the publication and promotion gender gaps.

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A Appendix

A.1 Descriptive statistics

Table A1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A	All	Women	Men	Diff.	Junior	Senior	Diff.
Observations	42790	10696	32094		21564	21226	
Woman	0.250				0.326	0.172	-0.154^a
	(0.433)				(0.469)	(0.378)	(0.004)
Age	45.2	41.7	46.3	4.6^a	37.0	53.5	16.4^a
	(9.6)	(9.5)	(9.4)	(0.1)	(4.9)	(5.2)	(0.0)
Prob. to publish	0.337	0.300	0.353	0.053^a	0.429	0.248	-0.181^a
	(0.473)	(0.458)	(0.478)	(0.005)	(0.495)	(0.432)	(0.004)
Quantity	0.283	0.188	0.326	0.138^a	0.359	0.223	-0.136^a
	(1.024)	(0.619)	(1.205)	(0.012)	(1.019)	(1.154)	(0.011)
solo-authored	0.184	0.116	0.216	0.100^a	0.227	0.154	-0.073^a
	(0.902)	(0.546)	(1.068)	(0.011)	(0.887)	(1.037)	(0.009)
coauthored	0.098	0.072	0.110	0.038^a	0.132	0.069	-0.063^a
	(0.260)	(0.175)	(0.291)	(0.003)	(0.285)	(0.245)	(0.003)
without peers	0.031	0.022	0.034	0.012^a	0.040	0.022	-0.018^a
	(0.336)	(0.189)	(0.404)	(0.004)	(0.368)	(0.359)	(0.004)
with peers	0.068	0.051	0.077	0.026^a	0.093	0.047	-0.046^a
	(0.352)	(0.213)	(0.426)	(0.004)	(0.397)	(0.371)	(0.004)
at least 1 woman	0.016	0.017	0.016	-0.001	0.022	0.010	-0.012^a
	(0.154)	(0.120)	(0.165)	(0.002)	(0.184)	(0.120)	(0.002)
only male peers	0.052	0.034	0.060	0.026^a	0.070	0.037	-0.034^a
	(0.316)	(0.178)	(0.391)	(0.004)	(0.352)	(0.350)	(0.003)
Panel B	All	Succ. cand.	Other	Diff.	last ten	Other s.c.	Diff.
Observations	42790	2718	40072		919	1799	
Woman	0.250	0.266	0.248	-0.018^b	0.322	0.238	-0.084^a
	(0.433)	(0.442)	(0.432)	(0.009)	(0.468)	(0.426)	(0.018)
Age	45.2	36.2	45.8	9.5^a	37.1	35.8	-1.3^a
	(9.6)	(5.8)	(9.6)	(0.2)	(6.4)	(5.4)	(0.2)
Prob. to publish	0.337	0.728	0.314	-0.415^a	0.665	0.761	0.096^a
	(0.473)	(0.445)	(0.464)	(0.009)	(0.472)	(0.427)	(0.018)
Quantity	0.283	0.712	0.264	-0.448^a	0.512	0.813	0.301^a
	(1.024)	(1.314)	(1.067)	(0.021)	(0.957)	(1.453)	(0.053)
solo-authored	0.184	0.458	0.173	-0.286^a	0.334	0.522	0.188^a
	(0.902)	(1.163)	(0.948)	(0.019)	(0.873)	(1.282)	(0.047)
coauthored	0.098	0.253	0.091	-0.163^a	0.178	0.291	0.113^a
	(0.260)	(0.356)	(0.257)	(0.005)	(0.234)	(0.399)	(0.014)
without peers	0.031	0.084	0.027	-0.056^a	0.082	0.085	0.003
	(0.336)	(0.461)	(0.355)	(0.007)	(0.256)	(0.536)	(0.019)
with peers	0.068	0.170	0.063	-0.106^a	0.097	0.207	0.110^a
	(0.352)	(0.521)	(0.372)	(0.008)	(0.262)	(0.609)	(0.021)
at least 1 woman	0.016	0.055	0.014	-0.041^a	0.021	0.072	0.052^a
	(0.154)	(0.346)	(0.132)	(0.003)	(0.116)	(0.416)	(0.014)
only male peers	0.052	0.115	0.050	-0.065^a	0.076	0.135	0.059^a
	(0.316)	(0.390)	(0.348)	(0.007)	(0.235)	(0.448)	(0.016)

Notes: Difference between women and men (column 2 to column 4 of panel A), between junior and senior (column 5 to column 7 of panel A), successful candidates and other researchers (column 2 to column 4 of panel B) and between those ranked last ten and other successful candidates (column 5 to column 7 of panel B). Succ. cand.: successful candidates in the contest divided between those received 'last ten' in the ranking and other successful candidates (s.c.). Standard errors in columns (4) and (7) and standard deviations in other columns in parentheses. ^{a}, ^{b}, ^{c} significant at the 1%, 5% and 10% level, respectively. Quantity: average annual number of published articles divided by the number of authors.

A.2 Robustness

A.2.1 Robustness of Table 3

Table A2: Table 3 with interacted individual-department fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Tot.	JEL	JEL	JEL	JEL	JEL
Number of peers	0.140	0.000	0.000	0.000	0.001	0.001
	(0.085)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Av. output of the peers	0.064	-0.000				
	(0.525)	(0.003)				
Av. output of the peers in JEL			0.625^a	0.697^a	0.609^a	0.702^a
			(0.035)	(0.034)	(0.029)	(0.029)
– × Woman				-0.330^a		-0.436^a
				(0.051)		(0.045)
– × Age					-0.022^a	-0.025^a
					(0.003)	(0.003)
R^2	0.50	0.10	0.12	0.12	0.12	0.13
Observations	41,731	771,498	771,498	771,498	771,498	771,498

Notes: See Table 3. All regressions include individual-department fixed effects.

Table A3: Table 3, controlling for the share of peers in JEL code and removing zeros

	Share of peers in JEL code			Removing zeros		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of peers	0.000	0.001	0.000	0.000	-0.000	-0.036^c
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.020)
% peers in JEL		0.253^a	0.031^b			
		(0.023)	(0.014)			
Av. output of the peers in JEL			0.586^a	0.805^a	0.957^a	0.669^a
			(0.048)	(0.034)	(0.051)	(0.134)
R^2	0.09	0.11	0.12	0.11	0.17	0.48
Observations	771,498	771,498	771,498	427,698	98,947	38,929

Notes: See Table 3. In column (4) observations corresponding to researchers who have never published in any JEL code are removed. In column (5) observations such that a researcher has never published in the JEL code under consideration are removed. If a researcher does not publish in that JEL code only in a single year, the observation is kept. In column (6) all zero observations are removed.

A.2.2 Robustness of Tables 4 and 5

Table A4: Table 4 with $\tau = t + 1$

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.004^{a}	0.004^{b}	0.004^{a}	0.004^{b}	0.002^{c}	0.003^{c}
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Av. output of the peers	0.452^{a}	0.433^{a}	0.485^{a}	0.599^{a}	0.404^{a}	0.428^{a}
	(0.062)	(0.140)	(0.058)	(0.160)	(0.057)	(0.146)
– × Woman			-0.134	-0.766^{a}		
			(0.090)	(0.169)		
– × Age					-0.031^{a}	-0.022
					(0.004)	(0.015)
R^2	0.05		0.05		0.05	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		20.3		10.0		10.7

Notes: See Table 4. The period to compute the peer variable is the following year instead of the average over the next three years.

Table A5: Table 5, with $\tau = t + 1$

	Single-author publications		Co-authored publications			
			With peers		Without peers	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.003^{a}	0.002^{c}	0.001^{c}	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Av. output of the peers	0.200^{a}	0.103	0.165^{a}	0.109	0.087^{a}	0.222^{b}
	(0.036)	(0.121)	(0.027)	(0.078)	(0.016)	(0.113)
R^2	0.03		0.04		0.04	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		20.3		20.3		20.3

Notes: See Table 5. The period to compute the peer variable is the following year instead of the average over the next three years.

Table A6: Table 4, with $\tau = t+1, t+2$

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.003^b	0.003^c	0.003^b	0.003^c	0.002	0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Av. output of the peers	0.415^a	0.379^b	0.448^a	0.527^a	0.368^a	0.376^b
	(0.059)	(0.149)	(0.056)	(0.168)	(0.054)	(0.155)
$-\times$ Woman			-0.138^c	-0.688^a		
			(0.078)	(0.197)		
$-\times$ Age					-0.032^a	-0.025^b
					(0.004)	(0.012)
R^2	0.08		0.08		0.08	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		20.1		9.9		10.9

Notes: See Table 4. The period to compute the peer variable is the next two year instead of the average over the next three years.

Table A7: Table 5, with $\tau = t+1, t+2$

	Single-author publications		Co-authored publications			
			With peers		Without peers	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.002^b	0.002	0.001^c	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Av. output of the peers	0.174^a	0.063	0.156^a	0.089	0.085^a	0.227^b
	(0.032)	(0.093)	(0.027)	(0.074)	(0.016)	(0.109)
R^2	0.05		0.06		0.07	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		20.1		20.1		20.1

Notes: See Table 5. The period to compute the peer variable is the next two year instead of the average over the next three years.

Table A8: OLS and IV separate regressions for men and women

	OLS		IV	
	(1)	(2)	(3)	(4)
	men	women	men	women
Number of peers	0.002	0.005^{b}	0.002	0.003
	(0.001)	(0.002)	(0.002)	(0.002)
Peers' productivity	0.400^{a}	0.346^{a}	0.424^{a}	-0.124
	(0.053)	(0.086)	(0.151)	(0.168)
R^2	0.10	0.09		
Observations	136,044	35,406	136,044	35,406
Kleibergen-Paap			26.4	32.7

Notes: See Table 4.

A.2.3 Robustness with different IV

Table A9: Table 4 keeping in the instrument all successful candidates except the first ten

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.002^{b}	0.002	0.002^{b}	0.002	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Av. output of the peers	0.371^{a}	0.294^{b}	0.415^{a}	0.415^{a}	0.351^{a}	0.279^{b}
	(0.044)	(0.133)	(0.048)	(0.160)	(0.041)	(0.129)
– × Woman			-0.181^{a}	-0.481^{a}		
			(0.065)	(0.114)		
– × Age					-0.025^{a}	-0.030^{a}
					(0.003)	(0.008)
R^2	0.08		0.08		0.09	
Observations	298,782	298,782	298,782	298,782	298,782	298,782
Kleibergen-Paap		25.6		13.3		13.0

Notes: See Table 4.

Table A10: Table 5 keeping in the instrument all successful candidates except the first ten

	Single-author publications		Co-authored publications			
			With peers		Without peers	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.001^{c}	0.001	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Av. output of the peers	0.151^{a}	0.059	0.131^{a}	0.090^{b}	0.088^{a}	0.145
	(0.024)	(0.063)	(0.021)	(0.039)	(0.016)	(0.088)
R^2	0.06		0.07		0.08	
Observations	298,782	298,782	298,782	298,782	298,782	298,782
Kleibergen-Paap		25.6		25.6		25.6

Notes: Table 5.

Table A11: Table 4 with output of peers defined using past production only

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.002^b	0.002	0.002^b	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Peers' productivity	0.232^a	0.175^b	0.247^a	0.240^b	0.193^a	0.164^c
	(0.035)	(0.088)	(0.036)	(0.098)	(0.032)	(0.088)
– × Woman			-0.066^c	-0.312^b		
			(0.038)	(0.124)		
– × Age					-0.019^a	-0.016^b
					(0.003)	(0.007)
R^2	0.09		0.09		0.10	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		31.0		15.4		16.1

Notes: See Table 4.

Table A12: Table 5 with output of peers defined using past production only

	Single-author publications		Co-authored publications			
			With peers		Without peers	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.002^b	0.001	0.001	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Peers' productivity	0.103^a	0.030	0.084^a	0.086^c	0.046^a	0.058
	(0.018)	(0.055)	(0.017)	(0.048)	(0.010)	(0.045)
R^2	0.07		0.08		0.09	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		31.0		31.0		31.0

Notes: See Table 5.

Table A13: Table 4 with journal-quality weighted publications

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.021	0.017	0.021	0.018	0.004	0.009
	(0.016)	(0.020)	(0.017)	(0.020)	(0.016)	(0.018)
Av. output of the peers	0.217^{b}	0.177	0.265^{b}	0.279	0.183^{b}	0.201
	(0.101)	(0.162)	(0.114)	(0.191)	(0.092)	(0.167)
– × Woman			-0.208^{b}	-0.514^{a}		
			(0.087)	(0.175)		
– × Age					-0.026^{a}	-0.018^{b}
					(0.004)	(0.009)
R^2	0.10		0.10		0.11	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		16.1		8.1		7.9

Notes: See Table 4.

Table A14: Table 5 with journal-quality weighted publications

	Single-author publications		Co-authored publications			
			With peers		Without peers	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.012	0.011	0.013^{b}	0.015	-0.005	-0.008
	(0.010)	(0.011)	(0.005)	(0.009)	(0.011)	(0.011)
Av. output of the peers	0.058	0.043	0.094^{a}	0.113	0.065	0.022
	(0.041)	(0.065)	(0.024)	(0.089)	(0.045)	(0.061)
R^2	0.07		0.08		0.09	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		16.1		16.1		16.1

Notes: See Table 5.

Table A15: Table 4 with alternative instrument

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.003[a]	0.002[c]	0.003[a]	0.002[c]	0.002[b]	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Av. output of the peers	0.389[a]	0.245	0.443[a]	0.374[b]	0.364[a]	0.248
	(0.031)	(0.160)	(0.035)	(0.175)	(0.029)	(0.162)
– × Woman			-0.216[a]	-0.481[a]		
			(0.052)	(0.125)		
– × Age					-0.023[a]	-0.017
					(0.003)	(0.010)
R^2	0.09		0.09		0.09	
Observations	406,944	406,944	406,944	406,944	406,944	406,944
Kleibergen-Paap		14.9		7.6		7.7

Notes: We reproduce exactly Table 4 with the alternative instrument using the peer closest to the department of interest, rather than the peer who actually joined, as an instrument for average output of the peers. See Table 4 for the rest of the details on the specification.

Table A16: Table 5 with alternative instrument

	Single-author publications		Co-authored publications			
			With peers		Without peers	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.002[b]	0.001	0.000	0.000	0.001[b]	0.001[c]
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Av. output of the peers	0.147[a]	-0.006	0.134[a]	0.102	0.109[a]	0.149[c]
	(0.017)	(0.078)	(0.016)	(0.080)	(0.012)	(0.078)
R^2	0.06		0.07		0.09	
Observations	406,944	406,944	406,944	406,944	406,944	406,944
Kleibergen-Paap		14.9		14.9		14.9

Notes: We reproduce exactly Table 5 with the alternative instrument using the peer closest to the department of interest, rather than the peer who actually joined, as an instrument for average output of the peers. See Table 5 for the rest of the details on the specification.

A.3 Clustered standard errors

Table A17: Table 4 with different levels of clustered standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.003	0.002	0.003	0.002	0.001	0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]
	{0.001}[a]	{0.001}[b]	{0.001}[a]	{0.001}[b]	{0.001}[c]	{0.001}
	(0.001)[b]	(0.001)[c]	(0.001)[b]	(0.001)[c]	(0.001)	(0.001)
Peers' productivity	0.385	0.306	0.418	0.414	0.341	0.316
	[0.055][a]	[0.140][b]	[0.061][a]	[0.152][b]	[0.049][a]	[0.141][b]
	{0.022}[a]	{0.097}[a]	{0.025}[a]	{0.105}[a]	{0.021}[a]	{0.096}[a]
	(0.053)[a]	(0.122)[b]	(0.051)[a]	(0.139)[a]	(0.049)[a]	(0.123)[b]
– × Woman			-0.140	-0.515		
			[0.099]	[0.185][b]		
			{0.044}[a]	{0.144}[a]		
			(0.065)[b]	(0.169)[a]		
– × Age					-0.030	-0.026
					[0.003][a]	[0.008][a]
					{0.002}[a]	{0.007}[a]
					(0.003)[a]	(0.008)[a]
R^2	0.10		0.10		0.10	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		[16.6]		[8.3]		[9.3]
Kleibergen-Paap		{32.4}		{16.2}		{17.4}
Kleibergen-Paap		(28.1)		(14.0)		(15.2)

Notes: See Table 4. Standard errors (and corresponding Kleibergen-Paap weak-instrument statistics) clustered by department between brackets, department-year between braces and department-JEL between parentheses.

Table A18: Table 5 with different levels of clustered standard errors

	Single-author publications		Co-authored publications			
			With peers		Without peers	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.002	0.001	0.001	0.001	-0.000	0.000
	[0.002]	[0.002]	[0.001][c]	[0.001]	[0.000]	[0.001]
	{0.001}[a]	{0.001}[c]	{0.000}[b]	{0.000}[c]	{0.000}	{0.000}
	(0.001)[b]	(0.001)	(0.001)[c]	(0.001)	(0.001)	(0.001)
Peers' productivity	0.157	0.037	0.145	0.136	0.083	0.133
	[0.021][a]	[0.069]	[0.038][a]	[0.074][c]	[0.022][a]	[0.078]
	{0.015}[a]	{0.054}	{0.017}[a]	{0.069}[c]	{0.009}[a]	{0.056}[b]
	(0.027)[a]	(0.073)	(0.029)[a]	(0.066)[b]	(0.016)[a]	(0.069)[c]
R^2	0.07		0.08		0.09	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		[16.6]		[16.6]		[16.6]
Kleibergen-Paap		{32.4}		{32.4}		{32.4}
Kleibergen-Paap		(28.1)		(28.1)		(28.1)

Notes: See Table 5. Standard errors (and corresponding Kleibergen-Paap weak-instrument statistics) clustered by department between brackets, department-year between braces and department-JEL between parentheses.

Table A19: Table 6 with different levels of clustered standard errors

Publications	All		Single author	Co-auth. w/o. peers	Co-authored with peers		
					All	1+ wom.	only men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of peers	-0.000	-0.000	-0.001	0.000	0.000	0.000	-0.000
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
	{0.001}	{0.001}	{0.000}	{0.000}	{0.000}	{0.000}^{b}	{0.000}
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Peer % women	0.003	0.003	0.001	0.001	0.001	0.001	0.001
	[0.003]	[0.003]	[0.002]	[0.001]	[0.001]	[0.000]	[0.001]
	{0.002}^{b}	{0.002}^{b}	{0.001}	{0.001}	{0.001}^{b}	{0.000}^{b}	{0.000}^{c}
	(0.002)^{c}	(0.002)^{c}	(0.001)	(0.001)	(0.001)^{b}	(0.000)^{b}	(0.001)
Male peers' prod.	0.464	0.524	0.230	0.184	0.110	0.008	0.102
	[0.045]^{a}	[0.048]^{a}	[0.030]^{a}	[0.020]^{a}	[0.017]^{a}	[0.003]^{a}	[0.015]^{a}
	{0.017}^{a}	{0.019}^{a}	{0.015}^{a}	{0.008}^{a}	{0.006}^{a}	{0.001}^{a}	{0.006}^{a}
	(0.040)^{a}	(0.044)^{a}	(0.030)^{a}	(0.014)^{a}	(0.013)^{a}	(0.003)^{a}	(0.012)^{a}
– × Woman		-0.276	-0.143	-0.088	-0.046	-0.003	-0.043
		[0.053]^{a}	[0.031]^{a}	[0.026]^{a}	[0.016]^{a}	[0.005]	[0.013]^{a}
		{0.022}^{a}	{0.015}^{a}	{0.011}^{a}	{0.007}^{a}	{0.003}	{0.006}^{a}
		(0.054)^{a}	(0.034)^{a}	(0.021)^{a}	(0.012)^{a}	(0.004)	(0.011)^{a}
Fem. peers' prod.	0.174	0.182	0.053	0.072	0.057	0.034	0.023
	[0.028]^{a}	[0.028]^{a}	[0.016]^{a}	[0.014]^{a}	[0.017]^{a}	[0.008]^{a}	[0.010]^{b}
	{0.012}^{a}	{0.014}^{a}	{0.010}^{a}	{0.007}^{a}	{0.007}^{a}	{0.004}^{a}	{0.005}^{a}
	(0.027)^{a}	(0.029)^{a}	(0.022)^{b}	(0.011)^{a}	(0.015)^{a}	(0.007)^{a}	(0.010)^{b}
– × Woman		-0.026	-0.012	-0.020	0.006	0.002	0.004
		[0.046]	[0.025]	[0.022]	[0.012]	[0.009]	[0.009]
		{0.024}	{0.015}	{0.010}^{b}	{0.008}	{0.006}	{0.007}
		(0.052)	(0.031)	(0.021)	(0.013)	(0.008)	(0.011)
R^2	0.12	0.12	0.07	0.11	0.08	0.06	0.07
Observations	771,498	771,498	771,498	771,498	771,498	771,498	771,498

Notes: See Table 6. Standard errors clustered by department between brackets, department-year between braces and department-JEL between parentheses.

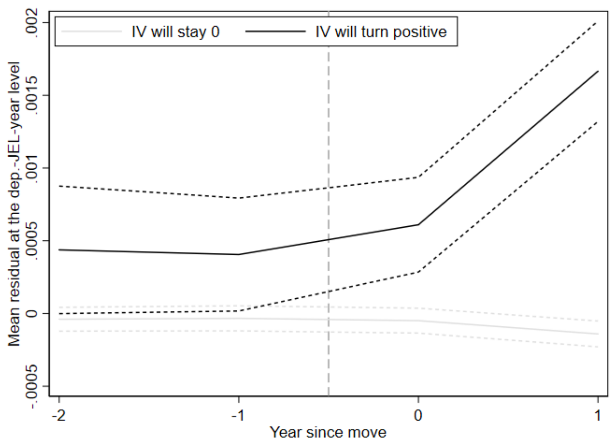
Table A20: Table 7 with different levels of clustered standard errors

	(1)	(2)	(3)	(4)
Number of peers	0.000	0.000	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]
	{0.000}	{0.000}	{0.000}	{0.000}
	(0.001)	(0.001)	(0.001)	(0.001)
Av. output of the peers in JEL	0.607	0.679	0.589	0.682
	[0.038]^a	[0.039]^a	[0.033]^a	[0.035]^a
	{0.015}^{a}	{0.017}^{a}	{0.014}^{a}	{0.016}^{a}
	(0.033)^a	(0.032)^a	(0.027)^a	(0.027)^a
– × Woman		-0.327		-0.432
		[0.056]^a		[0.050]^a
		{0.022}^{a}		{0.022}^{a}
		(0.051)^a		(0.046)^a
– × Age			-0.021	-0.024
			[0.003]^a	[0.003]^a
			{0.001}^{a}	{0.001}^{a}
			(0.003)^a	(0.003)^a
Av. output of the peers in other fields	-0.029	-0.032	-0.027	-0.032
	[0.004]^a	[0.004]^a	[0.004]^a	[0.004]^a
	{0.002}^{a}	{0.002}^{a}	{0.002}^{a}	{0.002}^{a}
	(0.004)^a	(0.004)^a	(0.004)^a	(0.004)^a
– × Woman		0.017		0.022
		[0.004]^a		[0.004]^a
		{0.002}^{a}		{0.002}^{a}
		(0.004)^a		(0.004)^a
– × Age			0.001	0.001
			[0.000]^a	[0.000]^a
			{0.000}^{a}	{0.000}^{a}
			(0.000)^a	(0.000)^a
R^2	0.12	0.12	0.12	0.12
Observations	771,498	771,498	771,498	771,498

Notes: See Table 7. Standard errors clustered by department between brackets, department-year between braces and department-JEL between parentheses.

A.4 Pre-trend analysis

Figure A1: Pre-trends



Notes: "Mean residual at the dep.-JEL-year level" defined as: average residual at the department-JEL code-year cell from a regression of individual JEL production in a given year (measured with a moving average of publications of the 3 following years) on age, individual, department and year-JEL fixed effects and the number of peers. "Year since move": defined as number of years compared to the date at which the successful candidate moved to the new university.

Table A21: Table 4 with department time trends

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Av. output of the peers	0.397[a]	0.301[b]	0.430[a]	0.412[a]	0.346[a]	0.300[b]
	(0.054)	(0.128)	(0.052)	(0.145)	(0.049)	(0.128)
– × Woman			-0.138[b]	-0.514[a]		
			(0.065)	(0.171)		
– × Age					-0.030[a]	-0.026[a]
					(0.004)	(0.008)
R^2	0.10		0.10		0.10	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		27.1		13.4		14.4

Notes: See Table 4.

A.5 Receivers and senders match based on age

Table A22: Peer effects and age, OLS

Publications	All		Single author	Co-auth. w/o. peers	Co-authored with peers		
					All	1+ wom.	only men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of peers	0.001	0.001	-0.000	0.000	0.001[c]	0.000[b]	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Peer % senior	0.002[c]	0.001	0.002[b]	-0.001	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Junior peers' prod.	0.258[a]	0.396[a]	0.150[a]	0.110[a]	0.136[a]	0.022[a]	0.088[a]
	(0.032)	(0.041)	(0.026)	(0.015)	(0.014)	(0.008)	(0.009)
– × Senior		-0.253[a]	-0.095[a]	-0.075[a]	-0.083[a]	-0.013[c]	-0.062[a]
		(0.040)	(0.028)	(0.009)	(0.013)	(0.007)	(0.007)
Senior peers' prod.	0.364[a]	0.425[a]	0.176[a]	0.087[a]	0.163[a]	0.016[a]	0.071[a]
	(0.029)	(0.042)	(0.024)	(0.015)	(0.017)	(0.005)	(0.013)
– × Senior		-0.144[b]	-0.026	-0.050[a]	-0.068[a]	-0.012[b]	-0.039[a]
		(0.058)	(0.034)	(0.015)	(0.020)	(0.005)	(0.014)
R^2	0.11	0.12	0.08	0.08	0.11	0.06	0.08
Observations	771,498	771,498	771,498	771,498	771,498	771,498	771,498

Notes: See Table 6.

A.6 First stages of the 2SLS

Table A23: First stages of Table 4

Dep. var.: av. output of the peers	–	–	× Woman	–	× Age
	(1)	(2)	(3)	(4)	(5)
Number of peers	-0.005[a]	-0.005[a]	-0.001[a]	-0.005[a]	-0.039[a]
	(0.002)	(0.002)	(0.000)	(0.002)	(0.015)
Av. output of sucessful cand.	0.047[a]	0.045[a]	-0.003[b]	0.047[a]	0.009
	(0.009)	(0.009)	(0.001)	(0.009)	(0.024)
– × Woman		0.007[a]	0.068[a]		
		(0.003)	(0.012)		
– × Age				-0.000	0.068[a]
				(0.000)	(0.012)
R^2	0.42	0.42	0.41	0.42	0.44
F	17.8	13.6	13.3	15.2	13.9
Observations	171,450	171,450	171,450	171,450	171,450

Notes: See Table 4. Column (1) is the first stage corresponding to column (2) of Table 4 and columns (2), (4) and (6) of Table 5. Columns (2) and (3) are the first stages corresponding to column (4) of Table 4. Columns (4) and (5) are the first stages corresponding to column (6) of Table 4.