Peer Effects in Academic Research: Senders and Receivers

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Abstract

Surprisingly, peer effects in academic research, in spite of their intuitive appeal, are rarely found to be empirically significant. Using an instrument based on a national contest in France determining researchers' location, we find evidence of peer effects when focusing on finer groups of senders and receivers, defined based on field of specialization, gender and age. Furthermore, we show that the match between the characteristics of senders and receivers plays a critical role. Men benefit a lot from peer effects provided by men, while all other types of gender combinations produce spillovers twice as small.

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1 Introduction

The production of academic knowledge seems to be organized so as to maximize peer effects: researchers are spatially clustered in academic departments, they interact in conferences and seminars and comment peers' work extensively during the production/publication process. Somewhat paradoxically, the empirical estimation of peer effects in academia has not provided supportive evidence. Two milestone contributions in this literature use natural experiments to establish the causal impact of "scientists' supply shocks". Waldinger (2012), exploit the dismissal of Jewish scientists by the Nazis to overcome the endogeneity problem due to sorting of researchers, while Borjas and Doran (2012), use the influx of mathematicians from the Soviet Union into the US following the collapse of the USSR. Neither paper finds empirical support for positive peer effects.[1]

We argue in this paper that the estimation of peer effects in academia depends critically on how the set of relevant peers is defined and in particular on the characteristics of both senders (producers of peer effects) and receivers (recipients of peer effects). Contrary to most of the literature, we first provide evidence of significant peer effects when restricting the peer group to scientists working in the same field of research. Our finding is supportive of the idea that spillovers are only present within finely defined groups.[2] Second, we show that the characteristics of senders and receivers, and the match between those, play a critical role, in particular gender and age. Women benefit much less from peer effects provided by men, and senior researchers mostly benefit junior colleagues.

Our identification strategy uses the particular (and peculiar) promotion system from assistant to full professorship for economists in France. The system consists of a centralized contest to fill a number of positions opened in different universities. Candidates are ranked

[1] 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.

[2] Azoulay et al. (2010) find strong evidence for peer effects when drastically restricting the extent of peer network to consist only of co-authors. Exploiting unexpected deaths of superstar scientists, they estimate a significant decrease of the productivity of their co-authors.

after a long examination spanning over a six-month period. Successful candidates 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 chosen option of candidates. We start by showing that the only (highly) significant factor determining choices of candidates is the geographic distance with the university of origin. In particular, the average quality of the university in the field of specialization of the individual does not seem to play any role.

Even though reverse causality due to endogenous location choices does not appear to be a major concern and non-random spatial sorting is also controlled for by individual and department fixed effects, we go further and design an even more stringent identification strategy, using the arrival of professors ranked among the last ten in the contest. Those have a very much restricted choice set (the last ten universities that have not been chosen when their turn comes). The idea is that the specialization of the new professor who arrives, 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 JEL code (our measure of research field) of the university in which they land.

Using this identification strategy, we confirm that peer effects remain elusive, when defining the relevant peer group as the entire department, as in the literature mentioned in the first paragraph. 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.

After having shown the empirical relevance of peer effects, the second part of the paper delves into their mechanisms. In particular, we differentiate the effect of peers' productivity on publication that are single-authored, co-authored with peers or co-authored without peers. 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. The source of these indirect peer effects could be twofold. Peers of high productivity could be considered as role models, institute good practices, or alternatively they could actively try to help others. The first type of effects should affect the group uniformly, and in particular should impact both single and co-authored publications in a similar way. The fact that these categories react differently suggests that peer effects are mostly driven by peers making active efforts to help certain colleagues (commenting on their papers or putting them in contact with researchers in other institutions working on similar topics), but not necessarily up to the point of becoming a co-author.

The last part of the paper provides novel evidence on the key role played by characteristics of the senders and receivers of peer effects. We show that senior researchers provide higher spillovers, and those peer effects benefit mostly younger 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 spillovers about twice as small. This is the main driver for the result that women on average receive lower peer effects. We discuss in the conclusion the policy implications for the publication and promotion gender gaps.

Gender-specific peer effects have been studied extensively in the literature on education, with mixed results. Ficano (2012) shows, for college academic outcomes, that the peer effects are characterized 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.[3] Regarding academic research, there is an extensive literature studying the productivity gap between men and women, but very little work on gender peer effects. 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

[3]Foster (2006) on the contrary finds little evidence of peer effects even when separated by gender. Hoxby (2000) finds some evidence of 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.

within 6 years than their male counterparts.

In addition to papers mentioned at the start of the introduction using natural experiments to identify the effect of researcher supply shocks (Waldinger, 2012; Borjas and Doran, 2012; Azoulay et al., 2010), there is a sizeable literature on research productivity in academia. Without the use of natural experiments, a prior literature finds weak evidence of peer effects (Dubois et al., 2014; Kim et al., 2011). 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. While we focus on studying the impact of different peer groups, part of the literature focuses 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. (2018) show that ties such as having done the PhD in the same institution or sharing advisors matter for knowledge flows.

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. Baseline results are provided in section 3. We study mechanisms behind our findings in section 4, and heterogeneity in effects in section 5, before concluding in section 6.

2 Data and institutional setting

2.1 Institutional setting

In the French public university system, the hiring and promotion of professors follows a very codified and centralized process. Recruitments at the assistant professor level (called maître de conférences in France) are decided by each university.[4] Maître de conférences is a

[4] 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.

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.[5] 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 according to their final ranking. Importantly, the university chosen by candidates could not turn them down. Candidates lower in the ranking could choose only a 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, including their "home" university (in which they had a position before the promotion).

Several features of this system are useful for the rest of the study. First, it implies that we observe exactly the choice set of individuals and their preferred option, which allows us to study the 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 organize teaching, but the deviations from the standard conditions are rare. This implies that we can control for most of the characteristics of the choices. Finally, the organization of the contest implies that candidates ending up low in the ranking have a restricted choice set. This is an attractive feature, which limits the possibility to sort on characteristics linked to productivity, exploited for identification.

[5] Bosquet et al. (2018) 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.

2.2 Data and descriptive statistics

Our data consists of 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)[6] for the years 1990-2005 (the same dataset is used by Bosquet and Combes, 2017, where a more complete description can be found). 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 'real' economics departments. Note that a few universities have several economics departments. We run regressions at the department level even when referring to a 'university' by slight abuse of terminology.[7] 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 for years 1991 to 2008, which includes the JEL code 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, 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 results for our main results varying the definition of τ in Appendix A.2.2. In line with

[6]Not all academic economics 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.

[7]A few academics are affiliated to more than one department, in which case their output is split across their various departments, and one individual observation for each department of theirs is considered in the estimations.

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 83 different departments.[8] Over our sample period, we use 7 contests for the instrument (see section 3.2), 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 publication records 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 productive. Moreover, the right part of Panel B, shows that those ranked among the last 10 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.

[8] The number of departments has been growing over our sample period, either because of creation of new departments 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.

3 Results

3.1 Peer effects in academia: initial evidence

We start by studying the effect of the number of peers and average peer quality on productivity, with the following specification, standard in the literature:[9]

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

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

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

where each individual j is observed from year $\underline{t}(j)$ to year $\overline{t}(j)$ years in our 1990-2008 sample, and $T(j) = \overline{t}(j) - \underline{t}(j) + 1$ is the length of the career of individual j within our observation period.[10] The idea of including the whole production of an individual is to restrict the variation of the peer effect variable over time to come entirely from the composition of the department as in Waldinger (2012).

In column (1) of Table 1, we see 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.[11] This absence of any effect holds in column (2) where

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

[10] When the lifetime productivity is measured at the JEL code level, $\underline{t}(j)$ is the date of the first publication in the JEL code, not the actual start of the career.

[11] To simplify interpretation, the number of peers variable is normalized by the average number of peers

the dependent variable is measured at the researcher-JEL code-year level, but keeping the peers' productivity variable at the aggregate level.

In column (3) we estimate equation (1) now with both the productivity of the individual y_{it} and of her peers $Y_{u(i)t}$ measured at the JEL code level. 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 0.688 additional 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. First, when running the analysis at the JEL code level, the dependent variable often takes zero values. Second, the degree of specialization of the university in the JEL code, that could imply a specific effort to promote the field, and not its peers' productivity in the JEL code could be the relevant channel of spillovers. Table A2 in Appendix A.2.1 shows that our results 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.[12] If anything, those robustness tests increase the magnitude of the peer effect.

Columns (1) to (3) show that academic researchers do benefit from positive peer effects but only from those working on similar topics to their own.[13] The final results presented in Table 1 start examining the heterogeneity of the effects, depending on the characteristics of the receiver, paving the way for our detailed analysis of this question in section 5. In column (4) we show that women benefit less from peer effects than men and column (5)

in the sample.

[12] 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. However they control neither for reverse causality nor peer effects.

[13] Waldinger (2012) also considers this possibility when he uses the scientists' specialization but finds no effect, either under OLS or IV strategies. Our definition of topics, exploiting JEL codes, is however finer than his. Borjas and Doran (2012) also works at the field level within mathematics (similar to JEL codes) and finds no evidence of spillovers. The shock they use is however very different from ours since it is the large shock of the influx of Soviet mathematicians that led to a large scale shift in the composition of academia in the US regarding mathematics.

Table 1: Peer effects on publications per year, OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Tot.	JEL	JEL	JEL	JEL	JEL
Number of peers	0.092^c	0.000	0.000	0.000	0.001	0.001^b
	(0.047)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Peers' tot. productivity	0.055	-0.001				
	(0.265)	(0.002)				
Peers' JEL productivity			0.688^a	0.767^a	0.672^a	0.773^a
			(0.019)	(0.020)	(0.017)	(0.019)
– × Woman				-0.360^a		-0.469^a
				(0.024)		(0.025)
– × Age					-0.024^a	-0.028^a
					(0.002)	(0.002)
Year dummies	X					
Year × JEL FE		X	X	X	X	X
R^2	0.41	0.09	0.11	0.12	0.12	0.12
Observations	42,521	771,498	771,498	771,498	771,498	771,498

Notes: All regressions include age, individual and department fixed effects. Standard errors clustered by university-year between brackets. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively. The number of peers is divided by its sample mean (67.6). Peers' productivity as defined in equation(2). Column (1) ('Tot.'): Data aggregated over all JEL codes. Columns (2) to (6) ('JEL'): Estimations at the JEL level. Age is centered with respect to the sample mean when interacted.

shows that older researchers benefit less than younger ones. Comparing a women to a men or a researcher to a researcher 30 year older divides the magnitude of the peer effect by two.

3.2 Exploiting the national competition

Two main concerns might affect that validity or our strategy for peer effects estimation. First, unobservable factors, at the university level, might affect both the production of a researcher and of her peers. Second, endogenous sorting might induce productive scientists to choose better departments in particular in their field of interest. This might lead us to overestimate peer effects[14]

We therefore build an identification strategy that exploits the national contest described in section 2.1. We start by providing suggestive evidence for the absence of endogenous

[14] Note that our results are robust to including match-specific (department times researcher) fixed effects, which should mitigate this effect. See Appendix Table A3, which reproduces Table 1 with match-specific fixed effects.

spatial sorting of researchers. In Table 2 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. Contrary to our main regressions, we can use the full set of contests here (no need to account for publication delays), including the 2006 and 2008 ones.[15]

In columns (1) and (2) we explain the location choice by the number of academics in the university and their average productivity, as in our main specification. Candidates appear to prefer universities with more peers and of higher average productivity. However, when we control in column (3) for the distance of the university under consideration with the university where the mover had her previous position and a dummy variable for this university, the effect of peers disappear. Distance also clearly has the largest explanatory power.

Table 2: Location choices

	All successul candidates			Last 10 only	
	(1)	(2)	(3)	(4)	(5)
Log Number of academics	0.298	0.157	-0.075	1.652	1.697
	(0.822)	(0.819)	(0.861)	(3.045)	(3.228)
Av. academics' productivity		6.514^a	3.173	10.416^c	-0.287
		(2.158)	(2.496)	(5.766)	(5.693)
University where ass. prof.			-1.526		-3.680
			(0.936)		(3.271)
Log Distance previous pos.			-1.000^a		-1.696^a
			(0.148)		(0.528)
Pseudo-R^2	0.15	0.16	0.33	0.38	0.55
Observations	2,814	2,814	2,814	406	406

Notes: Conditional logit estimated. All regressions include department fixed effects. Standard errors between brackets. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively. Av. academics' productivity: Average sum of publications of academics (discounted by publications' age with a logistic function), weighted by the specialization of successul candidates.

The results suggest that endogenous sorting based on scientific characteristics should not be a major issue, since the decisive driver of choices is geographical distance with the home

[15]For the columns with only the last ten ranked (4) and (5), building on those 9 contests, there are therefore $9 \times 54 = 486$ potential observations. In reality, some universities offer several jobs, and the actual number of observations drops to 406.

university.[16] We nevertheless use this national contest to build an identification strategy so as to estimate the causal effect of peers. We instrument the productivity of the peers at date t by the productivity of the successful candidates who join the department at date t through the contest. The identifying assumption is that the candidates do not take into account the projected trend in productivity of the department specific to their JEL codes or future changes at the university level when choosing their location. Results in Table 2 provide suggestive evidence backing this assumption. To make this assumption even more credible, we use only the candidates ranked among the last 10 in the contest who face an even more restricted choice set, and can be considered to arrive in the university quasi randomly. We provide robustness checks in Appendix A.2.3 using all successful candidates except those ranked among the first 10. Note that for the group of candidates ranked among the last 10, columns (4) and (5) of Table 2 show that the effect of geographic distance on location choices is even larger than for the overall pool of candidates and the productivity of peers matters even less.

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

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

where $\mathcal{A}_{u(i)t}$ is the set of successful candidates who were ranked among the last 10 in the contest and who arrived in university $u(i)$ at date t (if t even) or $t-1$ (if t odd) (the contest occurs every other year). $N^a_{u(i)t}$ is the cardinality of $\mathcal{A}_{u(i)t}$.

IV results are presented in Table 3. For each specification, we also present the OLS results when restricting the sample to the observations used in the IV regression.[17] The

[16] It can be argued that these results do not necessarily generalize to any pool of movers. Indeed, one of the particularities of the French system is that when these researchers move to their new university, they can after three years choose to move again. However it does give suggestive evidence that the scientific distance is not in general the main driver of academics' location choices in France after the contest we use to draw causal inference.

[17] Note that the OLS results on this restricted sample suggest lower peer effects than in Table 1. We are indeed restricting our sample to universities of lower quality since the better universities either do not open positions at the agrégation, since they know they can obtain professors through subsequent mobility, or if

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). 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 25% 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 3: Peer effects on publications per year, JEL, IV

	(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^b	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Peers' productivity	0.412^a	0.304^b	0.446^a	0.428^a	0.362^a	0.320^a
	(0.025)	(0.121)	(0.028)	(0.134)	(0.025)	(0.120)
$- \times$ Woman			-0.144^a	-0.594^a		
			(0.049)	(0.155)		
$- \times$ Age					-0.033^a	-0.029^a
					(0.003)	(0.009)
R^2	0.10		0.10		0.10	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		29.7		14.8		15.5

Notes: All regressions include age, year×JEL, individual and department fixed effects. Standard errors clustered by university-year between brackets. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively. The number of peers is divided by its sample mean (67.6). Peers' productivity as defined in equation(2). Age is centered with respect to the sample mean when interacted.

In columns (3) to (6) 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. For gender the results suggest that in fact women do not benefit at all from peer effects. This is confirmed in Appendix Table A6, where we estimate peer effects separately for men and women. While men significantly benefit from peers, the coefficient for women is not

they do, receive better ranked candidates.

significantly different from zero when instrumenting average peers' productivity. The impact of age is similar to the one obtained with OLS. We return to these gender and age specific effects in section 5.

4 Mechanisms

In this section we provide evidence on the mechanisms that underly the peer effects we identified. Peers could affect productivity through three main channels. First, peers are potential co-authors and in that sense can directly increase productivity. Second, 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, or putting researchers in contact with the relevant people in the profession. Third, peers can act as role models: peers can set the example in terms of research practices and create an environment that increases productivity.

Distinguishing the direct channel of co-authorship from the indirect ones can be easily done by distinguishing productivity in terms of publications co-authored with peers and those that are not. Distinguishing between the two indirect channels is more challenging, even though the distinction between single-author publications and other types of publications can give some hints.

Results in Table 4 suggest that direct co-authorship is not the central channel for spillovers. Column (3) shows that there is an effect of the average productivity of peers on the number of publications co-authored with peers. However this result is not robust to instrumentation as displayed in column (4). On the contrary, average productivity of peers affects co-authored papers without peers both in OLS (column 5) and in IV (column 6). According to the IV results, if peers publish an additional paper in the JEL code on average, this increases the number of co-authored papers without peers by 0.153.

The results show that the pool of peers generating spillovers is not restricted to the set of

Table 4: Splitting production in three categories

	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[a]	0.001[c]	0.001[b]	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Peers' productivity	0.173[a]	0.044	0.153[a]	0.107	0.087[a]	0.153[b]
	(0.017)	(0.061)	(0.019)	(0.071)	(0.010)	(0.070)
R^2	0.07		0.08		0.09	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		29.7		29.7		29.7

See Table 3.

co-authors, which differentiates us from the literature focusing on the network of co-authors (Azoulay et al., 2010, for instance). Clearly, indirect channels are at play. Regarding the source of these indirect spillovers, column (2) shows that there are no effects of peers on single-authored papers (although the OLS result in column (1) is significant). This suggests that peers acting as role models, which should affect both single and co-authored papers is not key.[18] The fact that the productivity of peers differentially affects these two types of publications indicates that the indirect effects are more likely due to peers directly providing inputs in on-going research. Indeed this mechanism requires an investment by the peers that can be directed towards particular individuals. It is possible that peers invest more in commenting papers that are co-authored, that often have more potential. Moreover, peers could put individuals in contact with potential co-authors outside the institution, thus directly generating a peer effect on co-authored publications (without peers).

[18] If anything role models should affect more single-authored papers than paper co-authored with non peers who won't be affected.

5 The appropriate match between senders and receivers

In this final part of the paper, we examine in more depth the heterogeneity of peer effects, depending 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 recipients, 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.[19] For instance, are men more likely to provide peer effects to men?

To answer this type of questions, 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 few women enter the contest.

Column (1) of Table 5 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 0.562 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 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. These results, and in particular the fact that men benefit more than women from peer effects provided by men, could explain a large part of the publication gap between men and women, that is also visible in our data (Table A1 shows that men publish nearly twice as much as women). We discuss this further in the conclusion.

We then break down the effect according to the type of publication, in the spirit of the

[19] 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.

Table 5: Peer effects on publications per year, gender mechanisms, JEL, 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^b	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peer % women	0.004^b	0.004^b	0.002	0.001	0.001^b	0.001^a	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Male peers' prod.	0.562^a	0.631^a	0.289^a	0.225^a	0.117^a	0.010^a	0.107^a
	(0.017)	(0.020)	(0.014)	(0.009)	(0.006)	(0.001)	(0.006)
– × Woman		-0.305^a	-0.159^a	-0.096^a	-0.050^a	-0.004	-0.046^a
		(0.024)	(0.017)	(0.012)	(0.007)	(0.003)	(0.007)
Fem. peers' prod.	0.209^a	0.222^a	0.066^a	0.090^a	0.065^a	0.035^a	0.030^a
	(0.014)	(0.016)	(0.010)	(0.007)	(0.008)	(0.004)	(0.005)
– × Woman		-0.038	-0.019	-0.025^b	0.006	0.002	0.004
		(0.025)	(0.016)	(0.011)	(0.008)	(0.005)	(0.007)
R^2	0.11	0.11	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: All regressions include age, year×JEL, individual and department fixed effects. Standard errors clustered by university-year between brackets. ^{a}, ^{b}, ^{c} indicate significance at the 1%, 5% and 10% level, respectively. The number of peers is divided by its sample mean (67.6). Male and fem. peers' prod.: Average number of publications per year of male and female peers, respectively (in the field, among all departments' members, calculated over lifetime of each individual). The variation in average peers' productivity hence comes from the changes of the compositions of the departments. Column (6) computes individual productivity based on publications co-authored with peers among whom there is at least a woman and column (7) when all peer co-authors are men.

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 0.289, 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 the peers are male on a co-authored publication, men benefit much more than women from peer effects.

Table 1, in addition to the role of gender of the recipient, had also highlighted the role of age. We now explore whether match specificities also matter in the case of age. Distinguishing between junior researchers and senior researchers, we show in Appendix Table A9 column (1) that senior researchers provide higher levels of peer effects than younger ones. 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, this results highlight the particular importance of the characteristics of the match between sender and receiver.

6 Conclusion

This article shows that peer effects in academia are present and large within precisely defined fields and for some groups of researchers, defined based on gender and age. We find that another important component of peer effects is the match between receivers and senders. 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.

Our results have policy implications for the organization of academia. First, they highlight the value of specialization 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 (Bosquet et al., 2018) between women and men observed in academia. The fact that women benefit less from peer effects produced by men, can explain part of this publication gap. 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 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 stories; 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	42,790	10,696	32,094		21,564	21,226	
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 10	Other s.c.	Diff.
Observations	42,790	2,718	40,072		919	1,799	
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)	(0.347)	(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 10 and other successful candidates (column 5 to column 7 of Panel B). Succ. cand.: successful candidates in the contest divided between those received 'Last 10' in the ranking and other successful candidates (s.c.). Standard errors in columns (4) and (7) and standard deviations in other columns in brackets. ^{a}, ^{b}, ^{c} significant at the 1%, 5% and 10% level, respectively.

A.2 Robustness

A.2.1 Robustness of Table 1

Table A2: Robustness of Table 1, 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^a
	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.014)
% peers in JEL		0.224^a	0.078^b			
		(0.033)	(0.032)			
Peers' JEL productivity			0.682^a	0.892^a	1.062^a	0.740^a
			(0.019)	(0.023)	(0.038)	(0.072)
R^2	0.09	0.10	0.11	0.11	0.17	0.48
Observations	771,498	771,498	771,498	427,698	98,947	38,929

Notes: All regressions include age, year×JEL, individual and department fixed effects. Standard errors clustered by university-year between brackets. ^{a}, ^{b}, ^{c} Significant at the 1%, 5% and 10% level, respectively. The number of peers is divided by its sample mean (67.6). Peers' productivity as defined in equation(2).

Table A3: Robustness of Table 1, with interacted individual×department fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Tot.	JEL	JEL	JEL	JEL	JEL
Number of peers	0.140^a	0.000	0.000	0.000	0.001	0.001^c
	(0.044)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Peers' tot. productivity	0.064	-0.000				
	(0.252)	(0.003)				
Peers' JEL productivity			0.690^a	0.772^a	0.674^a	0.779^a
			(0.019)	(0.020)	(0.017)	(0.019)
– × Woman				-0.376^a		-0.489^a
				(0.025)		(0.025)
– × Age					-0.025^a	-0.028^a
					(0.002)	(0.002)
Year dummies	X					
Year × JEL FE		X	X	X	X	X
R^2	0.50	0.10	0.12	0.12	0.12	0.12
Observations	41,731	771,498	771,498	771,498	771,498	771,498

Notes: All regressions include age and individual×department fixed effects. Standard errors clustered by university-year between brackets. ^{a}, ^{b}, ^{c} Significant at the 1%, 5% and 10% level, respectively. The number of peers is divided by its sample mean (67.6). Peers' productivity as defined in equation(2). Age is centered when interacted.

A.2.2 Robustness of Table 3

Table A4: Peer effects on publications per year, JEL, IV, $\tau = t + 1$

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.004^b	0.003^c	0.004^b	0.003^c	0.002^c	0.003
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Peers' productivity	0.491^a	0.469^c	0.526^a	0.666^b	0.438^a	0.460^c
	(0.043)	(0.241)	(0.046)	(0.283)	(0.041)	(0.245)
− × Woman			-0.143	-0.907^a		
			(0.087)	(0.259)		
− × Age					-0.034^a	-0.025
					(0.005)	(0.018)
R^2	0.05		0.05		0.05	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		21.8		10.7		11.1

Notes: All regressions include age, year×JEL, individual and department fixed effects. Standard errors clustered by university-year between brackets. [a], [b], [c] Significant at the 1%, 5% and 10% level, respectively. The number of peers is divided by its sample mean (67.6). Peers' productivity as defined in equation(2). Age is centered with respect to the sample mean when interacted.

Table A5: Peer effects on publications per year, JEL, IV, $\tau = t + 1, t + 2$

	(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^b	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Peers' productivity	0.448^a	0.415^b	0.482^a	0.590^a	0.394^a	0.409^b
	(0.032)	(0.167)	(0.035)	(0.185)	(0.031)	(0.174)
− × Woman			-0.142^b	-0.813^a		
			(0.062)	(0.193)		
− × Age					-0.035^a	-0.030^b
					(0.004)	(0.013)
R^2	0.08		0.08		0.08	
Observations	171,450	171,450	171,450	171,450	171,450	171,450
Kleibergen-Paap		22.7		11.2		11.8

Notes: see Table A4.

Table A6: Robustness of Table 1, separate regressions for men and women

	OLS		IV	
	(1)	(2)	(3)	(4)
	men	women	men	women
Number of peers	0.002^c	0.005^a	0.002^c	0.003^c
	(0.001)	(0.002)	(0.001)	(0.002)
Peers' productivity	0.425^a	0.381^a	0.439^a	-0.187
	(0.028)	(0.047)	(0.147)	(0.180)
R^2	0.10	0.09		
Observations	136,044	35,406	136,044	35,406
Kleibergen-Paap			28.2	35.2

Notes: see Table A4.

A.2.3 Robustness with different IV

Tables A7 and A8 below reproduce Tables 3 and 4 dropping the first ten successful candidates of each contests to construct the instrument (instead of keeping the last ten).

Table A7: Peer effects on publications per year, JEL, IV

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Number of peers	0.002^a	0.002^b	0.002^a	0.002^b	0.001^b	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Peers' productivity	0.395^a	0.318^a	0.445^a	0.457^a	0.374^a	0.306^a
	(0.022)	(0.117)	(0.025)	(0.136)	(0.022)	(0.111)
– × Woman			-0.203^a	-0.556^a		
			(0.036)	(0.099)		
– × Age					-0.028^a	-0.035^a
					(0.002)	(0.007)
R^2	0.08		0.08		0.09	
Observations	298,782	298,782	298,782	298,782	298,782	298,782
Kleibergen-Paap		45.5		23.3		22.9

Notes: All regressions include age, year×JEL, individual and department fixed effects. Standard errors clustered by university-year between brackets. [a], [b], [c] Significant at the 1%, 5% and 10% level, respectively. The number of peers is divided by its sample mean (67.6). Peers' productivity as defined in equation(2). Age is centered with respect to the sample mean when interacted.

Table A8: Splitting production in three categories

	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^b	0.001^c	0.000	0.000	0.000	0.001^c
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Peers' productivity	0.165^a	0.066	0.134^a	0.079^b	0.095^a	0.173^b
	(0.014)	(0.051)	(0.014)	(0.038)	(0.009)	(0.072)
R^2	0.06		0.07		0.08	
Observations	298,782	298,782	298,782	298,782	298,782	298,782
Kleibergen-Paap		45.5		45.5		45.5

See Table A7.

A.3 Match specificities in terms of age

Table A9: Peer effects on publications per year, age mechanisms, JEL, 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^{c}	-0.000	0.000^{b}	0.001^{a}	0.000^{a}	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peer % old	0.002^{b}	0.001^{c}	0.002^{a}	-0.001^{c}	0.000	-0.000	-0.000^{c}
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Junior peers' prod.	0.323^{a}	0.474^{a}	0.186^{a}	0.121^{a}	0.166^{a}	0.023^{a}	0.098^{a}
	(0.017)	(0.023)	(0.015)	(0.008)	(0.010)	(0.003)	(0.006)
– × Old		-0.276^{a}	-0.104^{a}	-0.081^{a}	-0.090^{a}	-0.014^{a}	-0.068^{a}
		(0.023)	(0.017)	(0.007)	(0.010)	(0.003)	(0.006)
Senior peers' prod.	0.423^{a}	0.494^{a}	0.213^{a}	0.092^{a}	0.189^{a}	0.016^{a}	0.076^{a}
	(0.018)	(0.031)	(0.020)	(0.009)	(0.013)	(0.003)	(0.008)
– × Old		-0.164^{a}	-0.031	-0.056^{a}	-0.077^{a}	-0.012^{a}	-0.044^{a}
		(0.039)	(0.024)	(0.009)	(0.016)	(0.003)	(0.008)
R^2	0.11	0.12	0.07	0.08	0.11	0.05	0.07
Observations	771,498	771,498	771,498	771,498	771,498	771,498	771,498

Notes: All regressions include age, year×JEL, individual and department fixed effects. Standard errors clustered by university-year between brackets. ^{a}, ^{b}, ^{c} Significant at the 1%, 5% and 10% level, respectively. The number of peers is divided by its sample mean (67.6). Junior and senior peers' prod.: Average number of publications per year of peers aged less and more than 45, respectively (in the field, among all departments' members, calculated over lifetime of each individual). The variation in average peers' productivity hence comes from the changes of the compositions of the departments. Column (6) computes individual productivity based on publications co-authored with peers among whom there is at least a woman and column (7) when all peer co-authors are men.