Social connections and editorship in economics

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Abstract. This paper investigates the determinants of editorial board membership, for 17 leading journals in economics, from 1997 to 2009. We find that the researcher's scientific profile and connections to the editors in charge are significant predictors of editorship. Ceteris paribus, after controlling for unobserved researcher heterogeneity, scholars with links to editors in the co-authorship network are more likely to serve as editors and this advantage decreases sharply with the social distance. Being a present or former departmental colleague or *protégé* of an editor-in-charge is positively associated with the probability of appointment to the board.

Résumé Liens sociaux et comités éditoriaux en économie. Cet article explore les éléments déterminants relatifs à la composition des comités éditoriaux de 17 revues économiques de premier plan entre 1997 et 2009. Nous avons constaté que le profil scientifique du chercheur ainsi que ses relations avec les éditeurs augmentent la probabilité d'être membre d'un comité éditorial. Toutes choses étant égales par ailleurs, et après avoir neutralisé l'hétérogénéité non observée des chercheurs, il apparaît que les chercheurs en lien avec des éditeurs dans un réseau de corédaction sont davantage susceptibles de devenir éditeurs à leur tour, et que cet avantage s'amenuise drastiquement avec la distance sociale. Le fait d'avoir été collègue au sein d'un même département ou mentoré par un éditeur est associé de façon positive à la probabilité d'intégrer le comité éditorial.

JEL classification: A11, J00, I23

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1. Introduction

The reputation of researchers is built on their past scientific achievements. Career progress, remuneration, research funding, scientific prizes and prestigious appointments all depend on reputation (Dasgupta and David 1994, Stephan 1996). In the case of prestigious appointments, a particularly relevant one is serving as editor of a leading scientific journal. Because it is editors who decide which scientific work should be published, they have substantial power over shaping the scientific progress of the discipline. They have the power to decide about which emerging research lines, methodologies, schools of thought and topics are worthy of publication (see Bedeian 2004, Crane 1967 and, more recently, Önder et al. 2018). Furthermore, editors' publication decisions can have an impact on the careers of other researchers and the success of entire departments and universities (Merton 1968, Heckman and Moktan 2020).

The extant literature focuses on how the chances of acceptance for journal publication depend on the author's social, geographical and institutional proximity to the editors in charge (Brogaard et al. 2014, Colussi 2018, Laband and Piette 1994, Medoff 2003, Wing et al. 2010) and how these editors' publication decisions affect the efforts and submission strategies of researchers (e.g., Baghestanian and Popov 2018). According to this stream of work, social connections between editors and authors foster authors' publication chances Despite the importance of the role of editor, few studies focus on analyzing board composition and on how editors are selected (Addis and Villa 2003, Bedeian et al. 2009, Metz and Harzing 2012).

In this paper, we investigate the chances of being selected to be an editor in the case of 17 leading journals, using an unbalanced panel of 31,909 researchers, observed between 1997 and 2009.

Our findings confirm the idea that editors are recruited based on their scientific career progress. However, we find, also, that social connections matter. Researchers with no links to any of the members of the editorial boards in the co-authorship network, have a small chance of being appointed editor, while for those with such links, the probability decreases with the distance from the editors. Similarly, a current or former affiliation with the same department as that of the editor in charge is positively associated with the probability of being appointed to the editorial board. Finally, board membership of the researcher's *mentor* is associated with a higher probability of being appointed.

We interpret our findings on the effects of social connections by considering their twofold role in the recruitment process. First, the recruitment committee might use social connections to gather information and reduce the information asymmetry problem. Editors-in-charge are able easily to observe the scientific curriculum of a potential editor, but this does not provide relevant details such as the researcher's contribution to the co-authored articles, the social impact of her research, her organizational and administrative skills or her potential commitment to the appointment. We conjecture that these characteristics are observable for socially connected researchers and that editors use this information to select the researcher with the best fit to the editorial job. Zinovyeva and Bagues (2015) propose a similar argument in the case of the relationship between hiring committees and candidates for academic positions.

Second, social connections might bias editors' decisions and lead them to use selection criteria not relevant for the editorial job. Editors-in-charge might favour researchers with a similar culture and values, namely those subscribing to the same school of thought, with similar background education and from the same institution as the editor. Relying on the homophily principle in social networks, that is, "people's personal networks are homogeneous with regard to sociodemographic, behavioral, and interpersonal characteristics" (McPherson et al. 2001, page 415), we expect editors in charge to search for scientists similar to themselves and to search mainly among those in their social network. Several studies of editors' publication decisions propose favouritism as a possible explanation of the higher chances of publication in a leading journal among authors socially connected to the editors (Laband and Piette 1994, Medoff 2003).

The argument related to possible use of social connections to gather information or exercise favouritism in editors' recruitment activity, mirrors the argumentation proposed by labour economists in relation to the role of referrals in the recruitment process. Employers might use referrals that make explicit the social ties between the referring and referred individuals, to gather information on worker quality not directly observable from the worker's resume (Burks et al. 2015, Montgomery 1991, Pallais and Sands 2016). Alternatively, nepotism might make employers more inclined to hire socially connected individuals (Wang 2013). Finally, they might prefer to hire referred workers because they are more likely to be similar to their referrers (Rees 1966). Most of the empirical evidence on the effect of referrals is based on low skilled labour markets where an employer higher up in the hierarchy decides about recruitment. From this perspective, our paper contributes to the *indirect* evidence provided by this literature strand (see Topa 2011), studying the case of journal editors who are highly skilled, are recruited by a committee of peers and for whom information on their entire professional history is available.

In addition to social connections, we consider determinants of the editorial appointment such as the researcher's biography, scientific productivity and field of expertise. Researchers appointed as editors need to be authoritative and require legitimation to be able make judgements about colleagues' work (Bedeian et al. 2009, Cole and Cole 1974). These characteristics can (at least partially) be deduced from their biographies. Moreover, scientists with documented capacity for conducting highlevel research are more entitled and more competent to judge the publishability of the submitted papers (Bedeian et al. 2009). Therefore, we consider the quantity and quality of scientists' publications as determinants of appointment as editor. Finally, researchers might be appointed based on their expertise in a field of (current or prospective) interest to the journal (Beauchamp et al. 2008). We consider the proximity of scientists' expertise to the journal specialization as a determinant of editorial appointment.

2. Data and methods

2.1. Data collection: Editors and eligible editors

To identify economists eligible for editorship we collected publication data related to 108 economics journals. We exploit the *American Economic Association* (EconLit) bibliometric database to gather information on the 58,939 articles published in these journals between 1997 and 2009 and use the papers published before 1997 to reconstruct the scientific profiles of older researchers. The 108 journals were selected according to the ranking proposed by Lee et al. (2010), which is based on bibliometric indicators and a broad definition of heterodox and mainstream journals. The list of the 30 journals with the largest number of published papers between 1997 and 2009 is reported in online appendix table A1.

We define a researcher as eligible for editorship at time t if she has been research active, that is, has had at least one article published in one of the 108 journals considered. Specifically, we assume a scientific career to begin with first publication in one of the 108 journals and to end three years after the last publication, after which time we assume that the researcher is no longer eligible for appointment as editor for a leading journal. We consider only authors with a career of at least four years and exclude a few cases of homonymy that we were unable to disambiguate and resulted in spurious careers longer than 55 years. We obtained an unbalanced panel of 31,909 researchers, present in the panel for an average of 5.50 years, during the period 1997 to 2009, with some 16.74% observed for 13 years. These researchers accounted for 44,711 published papers in the period from 1997 to 2009. The dataset covers a wide range of departments, with the researchers affiliated with 9,069 different institutions.

For information on editorial board composition for the leading journals, we collected editors' names for 17 journals recognized as leading journals according to several rankings (Card and DellaVigna 2013, Kalaitzidakis et al. 2003, Kodrzycki and Yu 2006, Stigler et al. 1995). Despite the many studies in this area, there is no universally accepted ranking. Table 1, column 1, presents the list of the selected leading journals. We reconstructed editorial board composition for each journal over 13 years from 1997 to 2009.

Standardized bibliometric datasets do not provide information on board composition (Kocher and Sutter 2001). For our analysis we exploited online archives and hard copies of the journal issues to create a database that includes the names of the principal and associate editors on their editorial boards, for the period 1997 to 2009. We were able to retrieve most of the

TABLE 1
Leading journals and number of editors by type

Journal	No. of articles 1997–2009	Number of distinct editors per journal	Average number of editors per year	Share of associate editors
American Economic Review	2,150	148	43.69	0.92
Econometrica	693	120	44.92	0.88
Economic Journal	820	67	15.77	0.88
International Economic Review	541	52	18.00	0.68
Journal of Econometrics	1,215	75	40.54	0.87
Journal of Economic Literature	275	76	27.62	0.92
Journal of Economic Perspectives	638	59	14.23	0.81
Journal of Finance	809	100	31.77	0.96
Journal of Financial Economics	762	49	27.85	0.72
Journal of Human Resources	383	32	12.77	0.00
Journal of Industrial Economics	246	98	33.15	0.69
Journal of Political Economy	858	15	3.08	0.00
Journal of Public Economics	1,176	88	34.77	0.67
Quarterly Journal of Economics	501	56	23.00	0.87
RAND Journal of Economics	417	54	23.77	0.70
Review of Economic Studies	589	114	37.85	0.65
Review of Economics and Statistics	742	90	40.69	0.83
Total for the 17 leading journals	**12,815**	**902**	**27.85**	**0.78**
Total sample of 108 journals	**44,711**			

NOTES: The 17 economics journals listed are identified as leading journals in our analysis. The first column, *No. of articles*, reports the number of articles published in each journal in the period 1997–2009 by the 31,909 researchers included in our analysis. *Number of distinct editors per journal* is the number of researchers who served as principal or associate editors in the period 1997–2009, *Average number of editors per year* is the board size. *Share of associate editors* is calculated as the ratio between the average number of associate editors per year and *Average number of editors per year*. In the case of *Journal of Political Economy*, we have no data for 1998–2001. *Journal of Political Economy* and *Journal of Human Resources* provide information on principal editors only. The last row of the table reports the number of articles in the 108 journals (leading and non-leading).

editors' names and were able to classify them as principal or associate editors. However not all journals systematically list all of the editors. For instance, the *Journal of Political Economy* reports only the names of the principal editors, while the *American Economic Review* lists more than 40 names, including both principal and associate editors. Also, it is sometimes difficult to classify editors as principal or associate (Addis and Villa 2003). In our principal editor category, we include researchers described as: editors, editors in chief, co-editors, managing editors, founding editors and advisory editors. In the associate editor category, we include those listed as board of editors, associate editors and advisory board. We dropped (if listed) the categories of editorial secretary, book review editor, business manager, editor's staff, advertising managers and editorial assistants.

It can be seen from the heterogeneous terms used to describe the researcher's contribution to board activities that distinguishing between editors involved in the scientific process of paper selection and those with administrative duties is not always clear-cut. To overcome this limitation, we include in our analysis only editors fitting our definition of researchers eligible for editorship, that is, editors who have published at least one article and who have a scientific career spanning at least four years since the date of this first publication. This reduces the initial list of 908 board members reported in the 17 leading journals between 1997 and 2009, to 902 editors who also are active researchers (99.3%).

Table 1 presents descriptive statistics for the leading journals.

Overall, 902 (about 2.8%) of the 31,909 researchers have served, at least once, as the editor of a leading journal during the period from 1997 to 2009. If we focus on researchers appointed at least once as principal editors (i.e., excluding associate editors), the percentage drops to about 0.9% (285 out of 31,909).

2.2. Determinants of editorship

Our empirical analysis estimates the probability for the researcher i in year t to be a member of the editorial board of at least one leading journal as a function of her characteristics. We define the variable $Editor_{it}$ as a dummy that equals 1 if researcher i is an editor of one of the 17 leading journals in year t, and 0 otherwise. As the determinants of editorial board membership, we look at variables for social connections (SC_{it}), scientific productivity (SP_{it}), field of expertise (FE_{it}) and personal biography (PB_{it}) of all the researchers i at time t, gathered in the vector $X_{it} = (SC'_{it}, SP'_{it}, FE'_{it}, PB'_{it})$. However, even controlling for this rich set of characteristics included in X_{it}, the probability of the individual's appointment to editor may still be correlated over time. We deal with this by employing the following two strategies: (i) we estimate $\Pr(Editor_{it} = 1|X_{it})$ using a pooled logit model with standard errors clustered at the researcher level and (ii) we estimate $\Pr(Editor_{it} = 1|X_{it}, \alpha_i)$ using a fixed effect logit model, where α_i is an individual time-invariant unobservable component potentially correlated to the Xs. Both methods have advantages and disadvantages. The pooled logit model does not consider the presence of α_i (which captures unobservable futures such as ability, motivation, engagement in editorial activity and social skills), but its estimation does not rely on the assumption of strict exogeneity of Xs and it exploits the entire available sample. The fixed effects logit model considers the presence of α_i, but its estimation requires strict exogeneity of Xs and uses only a limited part of the available sample. We acknowledge, also, that some time variant unobservable factors might still be omitted and potentially correlated with Xs: should this be the case, both the estimates would be biased.

In principle, researcher characteristics might affect the probability of appointment to principal editor and associate editor in different ways. To check whether this is the case, in section 3, we run two separate regression exercises with the respective dummy dependent variables $Principal\ editor_{it}$ (which equals 1 if researcher i is principal editor in year t) and $Associate\ editor_{it}$, (which equals 1 if the researcher is associate editors in year t).

2.2.1. Social connections

We measure researcher's social connections to the editor in charge using four variables: *Not connected to editors*, *Minimum distance from editors*, *Same department* and *Mentor–protégé*.

We consider the distance between the researcher and the pool of editors in charge in the co-authorship network (Brogaard et al. 2014). We define the dummy *Not connected to editors* equal to 1 if in the previous three years the researcher had not links to an editor at any distance in the co-authorship network. Among those with links, we find great heterogeneity in terms of distance from editors, which we capture with the variable *Minimum distance from editors*. Specifically, we calculate the distance between researcher A and editor B as the length of the shortest path between them in the years $t-1$, $t-2$, $t-3$. A and B are at distance 1 if they co-authored a paper in the previous three years, at distance two if they have one co-author C in common but are not co-authors with each other, and so on. We define the *Minimum distance from editors* in year t as the shortest distance between researcher A and all the editors to whom she is connected in $t-1, t-2, t-3$.[1] For those researchers who are not connected the variable is set to 0.

A second dimension of social connections that we take into account is the relation *Mentor-protégé* between an editor in charge and the researcher (Colussi 2018, Laband and Lentz 1999, Zinovyeva and Bague 2015). We classify the researchers in two groups: senior researcher with a career spanning more than seven years and junior researcher with a career of less than five years in a given year t. If the scientist is a junior researcher and co-authors an article with a senior researcher, we consider this a *mentor–protégé* relationship. According to this definition, a researcher could have more than one mentor if she publishes with more than one senior researcher. Also, the researcher might be alternately protégé and mentor in different phases of her career. In line with these definitions, we calculate a dummy variable (*Mentor–protégé*) that equals 1 if at least one mentor of the researcher is editor for one of the leading journals.

We consider the same affiliation between researcher and editor to account for the possible effect of being (or having been) a departmental colleague of an editor (Colussi 2018, Zinovyeva and Bagues 2015). The dummy variable *Same department* equals one when the editor is appointed, if the appointment starts after the researcher has joined the same department of the (will be) editor or when the researcher joins the department if the editor was already in charge.

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1 To construct the co-authorship network for years t = 1997, 1998 and 1999, we reconstructed the co-authorship network using the 8,027 articles published in the 108 journals in the period 1994 to 1996 and retrieved editor names for the 17 top journals in the same period.

2.2.2. Professional biography

We control for possible cohort effects (Hall et al. 2007) using a set of *Cohort of entry dummies* defined according to the year the researcher published her first article in one of the 108 journals in our list. Specifically, we define nine cohort dummies for researchers with first articles published before 1977, 1977 to 1985, 1986 to 1991, 1992 to 1995, 1996 to 1997, 1998 to 1999, 2000 to 2001, 2002 to 2003 and after 2003. We include a set of 13 *Year dummies* to capture possible time trends. Because *Length of the career in year t* is a linear combination of *Year* and *Cohort of entry dummies (Length of the career = t – Cohort of entry)* we cannot disentangle the effect of career length. Our specification implicitly attributes to differences between cohort of entry and calendar year any systematic variation of the editorship probability over the researcher's career not captured by the timevarying variables in X_{it}.

Affiliation with a prestigious university has been shown significant for publication (see Allison and Long 1990 and Clemente 1973), we propose two variables to capture prestige of the current affiliation and affiliation at the beginning of the research career. We consider top universities as those in the first 30 positions in the 2009 Shanghai social sciences ranking.[2] The criteria considered in the Shanghai ranking include universities' research outcomes, in terms of quality and quantity, and scientific prizes awarded to their affiliates and alumni. The appendix lists the 30 top universities according to the Shanghai ranking (online appendix table A2). We proxy prestige of the university that awarded the researcher's PhD degree on the basis of researcher's affiliation reported in the first publication (*PhD from a top university*). The dummy variable *Affiliation to a top university* equals 1 if the researcher was affiliated with a top university according to at least one article published in the previous three years.

Finally, we consider affiliation with two important economist networks *National Bureau of Economic Research* (NBER) and *Centre for Economic and Policy Research* (CEPR) by employing a dummy variable that equals 1 when the researcher reports an affiliation as NBER or CEPR (*NBER/CEPR*).

2.2.3. Scientific productivity

The quantity and quality of the published articles are expected to determine editorship (Bedeian et al. 2009). The articles published are proxies for researcher productivity and are the basis of the researcher's reputation in the scientific community. We use four variables to measure different dimensions of researcher productivity. The first is the flow of publications measured by the researcher's average number of publications per year in years $t-1$, $t-2$ and $t-3$ (*Average number of articles*). To account for reputation at the beginning of our period of observation, we calculate the stock of publications before 1997 (*Stock of articles published before 1997*). To measure the quality of the

2 Rankings available at `www.shanghairanking.com/FieldSOC2009.html`.

researcher's recent publications, we use the average of the maximum journal impact factor for the journals that published her work in years $t-1$, $t-2$ and $t-3$ (*Maximum impact factor*). We also define a dummy variable that equals 1 in year t if the researcher published at least one article in one of the 17 leading journals during years $t-1$, $t-2$ and $t-3$ (*At least one article in leading journals*).

In the case of articles with multiple authors it is difficult to identify each author's contribution (Lindsey 1982). Editors in charge may consider co-authored and single-authored articles differently. We control for this by calculating the researcher's number of co-authors in $t-1$, $t-2$ and $t-3$ (*Number of co-authors*) and defining a dummy variable *No co-authors*, which takes the value 1 if the researcher has no co-authors. The same two variables can be interpreted as proxies of the researcher's capability to recruit reviewers. Researchers with a large pool of co-authors have information on a large set of potential reviewers, a characteristic that could be evaluated positively by an editor in charge (Bedeian 2004).

2.2.4 Field of expertise

We expect the proximity between the researcher's field of expertise and the specialisms related to the 17 leading journals to enhance the probability of being an editor. The leading journals publish papers on many topics, but not with the same frequency. Therefore, scientists with expertise in some research fields might be more in demand than others as members of the editorial board.

To control for scientist's expertise, we calculate a set of 20 *Field of expertise dummies* (one for each of the 20 one-digit JEL codes), which equal 1 at year t if the researcher published at least one article with that code in the previous three years, and 0 otherwise. Given the uneven distribution of researchers by field of expertise, after some experimentation, we include in the regression 10 *Field of expertise dummies* for the JEL codes C, D, E, F, G, H, I, J, L and O and collapse into a unique category all the remaining JEL codes (*Other codes*).

A finer measure of proximity of researcher's expertise to the journal specialization exploits the overlap between researcher field of expertise and the topics of the articles published by the journal. We construct the variable *Content shared with leading journals* as follows: for each researcher at year t, we list all the three-digit JEL codes reported in her publications at years $t-1$, $t-2$ and $t-3$. Then, we attribute to the researcher the share of articles published in the leading journals in $t-1$, $t-2$ and $t-3$ that included at least one of the JEL codes in the list.

The popularity of the subject within the discipline might enhance the probability of the researcher being appointed to editor. To account for the importance of the subject in the discipline as a whole, we create the dummy variable. *At least one discipline content*, which equals 1 if the researcher published at least one article in the previous three years on one of the most

TABLE 2
Description of dependent and independent variables

Variable	Description
Dependent variables	
Editor	Dummy variable; equals 1 if the researcher is an editor in charge in one of the leading journals in year t, 0 otherwise
Principal editor	Dummy variable; equals 1 if the researcher is a principal editor in charge in one of the leading journals in year t, 0 otherwise
Associate editor	Dummy variable; equals 1 if the researcher is an associate editor in charge in one of the leading journals in year t, 0 otherwise
Independent variables	
Professional biography	
Cohort of entry dummies	9 dummy variables, respectively, for the researchers having their first publication in the 108 observed journals before 1977, 1977–1985, 1986–1991, 1992–1995, 1996–1997, 1998–1999, 2000–2001, 2002–2003 and after 2003
PhD from a top university	Dummy variable; equals 1 if the researcher reports on her first publication an affiliation with one of the top 30 universities (per 2009 Shanghai rankings, `www.shanghairanking.com/FieldSOC2009.html`)
Affiliation with a top university	Dummy variable; equals 1 if the researcher is affiliated with one of the top 30 universities in $t-1$, $t-2$, $t-3$ (per 2009 Shanghai rankings)
NBER/CEPR	Step dummy; switches to 1 the first time the researcher reports an affiliation with NBER (National Bureau of Economic Research) or CEPR (Center for Economic Policy Research)
Scientific productivity	
Average number of articles	Average number of articles published by the researcher per year in the 108 journals in the last three years, $t-1$, $t-2$, $t-3$
Maximum impact factor	We calculate this variable in two steps; first, we take the highest impact factor of the journals where the researcher has published in years $t-1$, $t-2$ and $t-3$; then, we calculate the mean of the three values
At least one article in leading journal	Dummy variable; equals 1 if the researcher has published at least one article in the 17 leading journals in economics in $t-1$, $t-2$, $t-3$
Stock of articles published before 1997	Number of articles published by the researcher before 1997 in the 108 journals
No co-authors	Dummy variable; equals 1 if the researcher has no co-authors in $t-1$, $t-2$, $t-3$
Number of co-authors	Number of co-authors in $t-1$, $t-2$, $t-3$
Field of expertise	
Field of expertise dummies	10 dummy variables, one for each JEL code below; each dummy equals 1 if the researcher has published at least one article in $t-1$, $t-2$ and $t-3$ in the one-digit JEL code C, D, E, F, G, H, I, J, L or O, respectively; similarly, we define a further dummy variable that equals 1 if during the same period the researcher has published at least one article in one of the remaining JEL codes; the 11 dummy variables are not mutually exclusive and can equal 0 jointly

(*continued*)

TABLE 2
(*Continued*)

Variable	Description
At least one article in heterodox journal	Dummy variable; equals 1 if the researcher published at least one article in a heterodox journal in $t-1$, $t-2$ and $t-3$; heterodox journals are a subsample of the 108 covered journals (see Lee et al. 2010 for the list of heterodox journals considered)
Content shared with leading journals	The variable is calculated in year t as the share of articles published in the 17 leading journals in $t-1$, $t-2$ and $t-3$ reporting at least one of the three-digit JEL codes used in the researcher's publications during the same time span; variable can take value ranging from 0 to 100
At least one discipline content	Dummy variable; equals 1 if the researcher has published at least one article with a subject in the highest 20th percentile of most frequent subjects treated in the universe of 108 journals in $t-1$, $t-2$ and $t-3$; subjects are identified according to the three-digit standard JEL codes reported on publications
Social connections	
Not connected to editors	Dummy variable; equals 1 if the researcher is not connected in any way with the editors in charge in $t-1$, $t-2$ or $t-3$
Minimum distance from editors	Minimum distance between the researcher and the closest editor; we measure the minimum distance in the network of co-authorship in $t-1$, $t-2$ and $t-3$ as the shortest possible path from one node to another; for researchers not connected to editors, the variable is set to 0
Same department	Step dummy that switches to 1 in two cases: (i) it switches to 1 when the editor is appointed if the editor's appointment starts after the researcher has joined the same department and (ii) it switches to 1 if the researcher joins the department when the editor was already in charge
Mentor–protégé	Step dummy that switches to 1 when a mentor of the researcher is appointed as editor of one of the 17 leading journals; mentor is the senior scholar with whom the researcher co-published at the beginning of her career; in the case of more than one mentor assigned to the researcher, the dummy equals 1 when the first mentor is appointed
Other controls	
Year dummies	13 dummy variables, one for each calendar year from 1997 to 2009

NOTES: The table lists all the dependent and independent variables included in our regression exercise and provides a brief description of how each variable was calculated. Further details on the calculation and interpretation of the variables are reported in the main text.

TABLE 3
Descriptive statistics

	(1) Total mean	(2) SD	(3) Editors mean	(4) Non-editors mean
Dependent variables				
Editor	0.03	0.17	1.00	0.00
Principal editor	0.01	0.09	0.25	0.00
Associate editor	0.02	0.15	0.80	0.00
Independent variables				
Professional biography				
Length of the career in year t	16.17	11.47	18.35	16.10
Cohort of entry	1988.06	12.04	1985.72	1988.13
PhD from a top university	0.10	0.30	0.26	0.09
Affiliation to a top university	0.14	0.34	0.55	0.12
NBER/CEPR	0.05	0.22	0.37	0.04
Scientific productivity				
Average number of articles	0.42	0.51	1.19	0.40
Maximum impact factor	0.34	0.53	1.26	0.32
At least one article in leading journals	0.23	0.42	0.81	0.21
Stock of articles published before 1997	4.52	8.03	14.11	4.23
No co-authors	0.48	0.50	0.16	0.49
Number of co-authors	1.09	1.51	2.80	1.04
Field of expertise				
At least one article in heterodox journals	0.15	0.36	0.04	0.16
Content shared with leading journals	0.57	0.85	1.42	0.54
At least one discipline content	0.16	0.36	0.26	0.15
Social connections				
Not connected to editors	0.83	0.38	0.39	0.84
Minimum distance from editors	0.46	1.30	0.94	0.44
Same department	0.49	0.50	0.95	0.47
Mentor–protégé	0.08	0.27	0.29	0.07
No. of observations	175,655		5,173	170,482

NOTES: The table presents the key figures for the 175,655 researcher–year pairs included the study sample (corresponding to 31,909 researchers). Specifically, it shows the mean and standard deviation (SD) of the dependent and independent variables grouped in four classes: *Professional biography*, *Scientific productivity*, *Field of expertise* and *Social connections*.

popular economics topics during the same period. We identify popular subjects as JEL codes in the top 20th percentile of the frequency distribution of the codes used by the 108 journals in $t-1$, $t-2$ and $t-3$.[3]

Because all 17 leading journals are mainstream journals, we include a dummy that equals 1 if the researcher recently published in one heterodox journal according to the definition in Lee et al. (2010) (*At least one article in heterodox journals*). Table 2 presents the variable definitions.

2.3 Descriptive statistics

Table 3 presents the descriptive statistics. Career length at time t ranges from four to 55 years, with an average of 16.16 years. The average author produc-

3 The list includes on average 14.23 distinct subjects per year.

TABLE 4
Researchers' field of expertise and share of article by field published by the 17 leading journals

	C	D	E	F	G	H	I	J	L	O	Others
	Researcher *field of expertise* (%)										
Whole sample (175,655 researcher–year)	5.24	8.18	6.12	5.43	7.74	3.62	3.85	7.52	7.35	7.53	14.88
Editors (5,173 editor–year)	17.20	20.94	11.41	6.32	17.13	9.45	5.20	15.19	16.01	8.35	12.00
Non-editors (170,482 (non-editor)–year)	4.88	7.80	5.96	5.40	7.46	3.44	3.81	7.29	7.08	7.51	14.97
	Share of articles published by the 17 leading journals reporting the JEL code (%)										
	15.15	20.18	11.49	7.19	20.01	11.41	7.22	18.23	13.44	10.11	14.01

NOTES: The upper panel presents the means of the *Field of expertise* dummy variables, for all 175,655 researcher–year pairs in the sample, the 5,173 editor–year pairs and the remaining 170,482 (non-editor)–year pairs. *Field of expertise* dummy variables are not mutually exclusive (authors can publish in more than one field) and all are equal to 0 for unproductive scientists. Therefore, the percentages in the upper panel do not sum to 100.

tivity is 0.42 articles per year; 10.6% (3,377 out of 31,909) of the researchers published their first article when affiliated with a prestigious department (corresponding to 9.8% of the researcher–year pairs in table 3) and 29.3% (9,347 out of 31,909) published an article in a heterodox journal (15.4% of the researcher–year pairs in table 3). 82.6% of the observations refer to researchers who were not connected to any editor in the previous three years, while 47.6% refer to researchers with no co-authors in the previous three years. Clearly, these two events are related, since a researcher with no co-authors is isolated in the co-authorship network and, therefore, has no links to any of the editors in charge. The overall average number of co-authors in the previous three years is 1.09, but if we restrict the sample to researchers with at least one co-authorship relation, the average almost doubles—to 2.09. The average distance from the closest editor, for those researchers connected to an editor at any finite distance, is 2.64 but drops to 0.46 if we include researchers with no links where the distance is set to 0.

Table 4 shows how the researchers in our sample are distributed according to field of expertise and compares their expertise with the share of articles published in the leading journals in the same field. Because the *Field of expertise* dummy variables are not mutually exclusive (authors may publish in more than one field) and all equal 0 for unproductive scientists, the means reported in the table do not sum to 100. For the entire sample, the dummy averages total 77.46% (i.e., at least 22.54% of the observations refer to scientists who did not publish in the previous three years). The most diffused field is *Microeconomics* (JEL code D), followed by *Financial Economics* (G); *Economic Development, Innovation, Technological Change, and Growth* (O); *Labor and Demographic Economics* (J) and *Industrial Organization* (L). The ranking changes with researcher's field of expertise for the most diffused codes in the leading journals (lower panel in table 4): codes J and G are the most diffused followed by D and C (*Mathematical and Quantitative Methods*).

If we compare the characteristics of the editors in charge with those of non-editor researchers (table 3, columns (3) and (4)), we see that editors are more productive (in terms of quality and quantity of publications), have longer careers, are more likely to be trained in a top institution and are less likely to publish in heterodox journals. Finally, editors are closer to other editors in charge along all the dimensions of social proximity considered. For instance, their probability to have links to other editors is higher than average for non-editor researchers. All the tests of mean equality between editors and non-editors (columns (3) and (4)) reject the null hypotheses.

Editors in charge are much more likely than non-editors to have expertise in fields D, C, G and L and less likely to have published articles with *Other JEL codes* in the previous three years (table 4). Not surprisingly, editor's field of expertise, measured by average JEL code dummy values, mimics the percentage of papers with the same codes published, in the leading journals.

3. Results

Table 5 presents the pseudo-maximum likelihood estimates of the pooled logit model (with standard errors clustered at the researcher level) and the conditional maximum likelihood estimates of the fixed effects logit model for the probabilities of being appointed editor, or principal or associate editor.

The estimations reported in column (1) of table 5 show that, for professional biography, ceteris paribus, researchers awarded a PhD from a prestigious university (*PhD from a top university*), affiliation with one of these universities in the previous three years (*Affiliation to a top university*) and being a member of NBER or CEPR (*NBER/CEPR*) all have a significantly higher probability to serve as editors. The *Cohort of entry* dummies show a significantly lower probability of editorship for younger researchers compared to the older ones (a graphical representation of the estimated coefficients is reported in online appendix figure A1).

As expected, more productive researchers have a higher chance of being editors. Both the quantity (*Average number of articles* and *Stock of articles published before 1997*) and quality (*Maximum impact factor* and *At least one article in leading journals*) of the published articles are positively associated with the probability of being an editor. The signs of the estimated coefficients of *No co-authors* and *Number of co-authors* suggest that incumbent editors assign more value to researcher who work either alone or in small teams.

Recent publication in a heterodox journal (*At least one article in heterodox journals*) is negatively associated with the researcher's chances of being an editor for a leading journal. This might be because incumbent editors are unwilling to appoint heterodox economists, but we cannot exclude that brilliant heterodox researchers are less interested in contributing to the management of leading mainstream economics journals. The parameter of the variable *Content shared with leading journals* is positive, that is, publishing on a subject that is highly relevant to the focus of the journal is associated with a higher probability of being an editor. This variable is positive if the researcher has *At least one publication in a leading journal*, which means that the coefficients of the two variables must be considered jointly. For the variable *At least one discipline content* we find a lower probability of being editor if the researcher publishes on subjects that are frequent in the whole discipline. If *At least one discipline content* equals 1, then for two thirds of these cases *Content shared with leading journals* is positive with a mean of 1.55. Here, the lower probability of being an editor associated with the variable *At least one discipline content*, is almost perfectly counterbalanced by the higher probability if the researcher's expertise is close to the journal specialization (proxied by *Content shared with leading journals*). We found only limited variation for the probability of being editor in the case of the field of expertise dummies and found no evidence of field-specific time trends (see online appendix figure A2).

TABLE 5
Determinants of editorial board membership, logit estimations

	Editor		Principal editor		Associate editor	
	Pooled (1)	Fixed effects (2)	Pooled (3)	Fixed effects (4)	Pooled (5)	Fixed effects (6)
Professional biography						
PhD from a top university	0.66^{***}		0.51^{**}		0.67^{***}	
	(0.12)		(0.23)		(0.12)	
Affiliation with a top university	0.23^{***}	-0.28^{***}	0.36^{**}	−0.26	0.18^{**}	-0.22^{**}
	(0.085)	(0.096)	(0.17)	(0.19)	(0.090)	(0.100)
NBER/CEPR	0.94^{***}	0.51^{***}	1.12^{***}	0.60*	0.79^{***}	0.53^{***}
	(0.10)	(0.17)	(0.18)	(0.34)	(0.11)	(0.18)
Scientific productivity						
Average number of articles	0.34^{***}	0.11	0.19^{*}	0.033	0.30^{***}	0.042
	(0.073)	(0.069)	(0.10)	(0.11)	(0.073)	(0.071)
Maximum impact factor	0.37^{***}	0.28^{***}	0.32^{***}	0.11	0.34^{***}	0.28^{***}
	(0.051)	(0.054)	(0.080)	(0.089)	(0.054)	(0.055)
At least one article in leading journals	1.05^{***}	−0.12	0.94^{***}	−0.36*	1.14^{***}	−0.048
	(0.078)	(0.087)	(0.15)	(0.18)	(0.086)	(0.091)
Stock of articles published before 1997	0.024^{***}		0.023^{***}		0.019^{***}	
	(0.0035)		(0.0042)		(0.0039)	
No co-authors	0.28^{***}	−0.12	0.23	-0.38^{*}	0.25^{***}	−0.060
	(0.085)	(0.10)	(0.17)	(0.21)	(0.091)	(0.11)
Number of co-authors	−0.034	0.073^{***}	−0.0092	0.10^{***}	-0.042^{*}	0.061^{***}
	(0.023)	(0.023)	(0.038)	(0.037)	(0.024)	(0.023)
Field of expertise						
At least one article in heterodox journals	-0.83^{***}	−0.23	-0.82^{***}	−0.25	-0.75^{***}	−0.24
	(0.14)	(0.16)	(0.26)	(0.30)	(0.15)	(0.16)
Content shared with leading journals	0.050^{***}	−0.019	0.053	0.0093	0.048^{**}	−0.013
	(0.019)	(0.021)	(0.033)	(0.036)	(0.021)	(0.021)
At least one discipline content	-0.15^{**}	0.0025	-0.21^{*}	0.080	−0.11	−0.026
	(0.077)	(0.084)	(0.12)	(0.15)	(0.082)	(0.086)
Social connections						
Not connected to editors	-0.89^{***}	-0.26^{***}	-1.09^{***}	−0.082	-0.75^{***}	-0.22^{**}
	(0.097)	(0.098)	(0.18)	(0.18)	(0.10)	(0.10)
Minimum distance from editors	-0.25^{***}	-0.10^{***}	-0.32^{***}	−0.060	-0.19^{***}	-0.076^{**}
	(0.031)	(0.030)	(0.063)	(0.062)	(0.031)	(0.031)
Same department	1.63^{***}	0.71^{***}	1.49^{***}	0.41	1.72***	0.68^{**}
	(0.19)	(0.26)	(0.42)	(0.65)	(0.20)	(0.26)
Mentor–protégé	0.64^{***}	1.06^{***}	0.75^{***}	1.14^{**}	0.59^{***}	0.72^{**}
	(0.11)	(0.33)	(0.21)	(0.55)	(0.12)	(0.31)
Constant	-5.68^{***}		-6.72^{***}		-6.07^{***}	
	(0.26)		(0.54)		(0.27)	
Cohort of entry dummies	Yes	No	Yes	No	Yes	No
Field of expertise dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year × *Field of expertise* dummies	Yes	Yes	Yes	Yes	Yes	Yes

(*continued*)

TABLE 5
(*Continued*)

	Editor		Principal editor		Associate editor	
	Pooled	Fixed effects	Pooled	Fixed effects	Pooled	Fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	175,655	8,889	175,655	3,408	175,655	8,431
No. of researchers	31,909	776	31,909	285	31,909	741
No. of researchers appointed at least in one year	902	776	303	285	816	741
Pseudo R2	0.355	0.052	0.336	0.091	0.317	0.042

NOTES: The table presents the estimated coefficients of the probability of being editor, principal editor or associate editor. Columns (1), (3) and (5) refer to the pooled logit models, while columns (2), (4) and (6) refer to the fixed effects logit models. When applying fixed effects, e.g., in column (2), the number of researchers drops from 31,909 to 776 because all those researchers not appointed to an editorship during the study period (31,007) or those who are editors throughout (126) are excluded from the estimation sample. The remaining 776 researchers are those where we observe a change in editorship status during the study period. Similarly, in columns (4) and (6), we observe a drop in the number of observations. The number of researchers appointed at least in one year in columns (3) and (5) do not sum to those in column (1) because the same researcher can be appointed as both associate and principal editor during her career (and similarly for columns (2), (4) and (6)). Standard errors are in parentheses, clustered at researcher level for the pooled logit models. Significance levels at ***p<0.01, **p<0.05, *p<0.1.

Connections to board members are important. Ceteris paribus, no links (at any distance) to any members of any boards in the co-authorship network (*Not connected to editors*) is associated with a lower chance of being an editor. Among researchers that do have links, the probability decreases with distance from editors in the co-authorship network (*Minimum distance from editors*). A researcher with a distance of four from an editor has the same chance of becoming an editor as a researcher with no links.[4] To compare the relevance of social ties to productivity factors, consider that, ceteris paribus, a scholar with no links to an editor in the co-authorship network, but with at least one article published in one of the leading journals in the previous three years has the same chance of appointment to an editorial board as a researcher who has an editor co-author but no publications in a leading journal.[5] Equivalently, having three more published articles per year, compensates a disconnected scholar for this lack of connections.[6]

4 We cannot reject the null hypothesis that four times the coefficient of the variable *Minimum distance for editors* (−0.25) is equal to the coefficient of the variable *Not connected to editors* (−0.89, p-value 0.28).

5 We cannot reject the null hypothesis that the sum of the coefficient of the variable *At least one article in top journals* (1.05) and the coefficient of the variable *Not connected to editors* (−0.89) equals 0 (p-value 0.23).

6 We cannot reject the null hypothesis that the sum of three times the coefficient of the variable *Average number of articles* (3×0.34) and the coefficient of the variable *Not connected to editors* (−0.89) equals 0 (p-value 0.62).

The results of simple statistical tests applied to the estimated coefficients, show that being or having been affiliated with the same department as an editor in charge (*Same department*) is as relevant as having around five (4.9) more publications per year (*Average numbers of articles*). Researchers whose (proxied) mentors are board members (*Mentor–protégé*) have an advantage over other scholars, equivalent to 1.9 additional publications per year in the previous three years (*Average numbers of articles*).

If we consider the probability of editorship conditional on the unobserved fixed effects (table 5, column (2)), the results for some variables change. Here, all the time-invariant variables are dropped and the number of researchers is reduced to 776, since focusing on within-individual differences restricts the sample to those authors who changed their editor status at least once in the 13-year period considered. In other words, we drop the 126 (902 minus 776) researchers who are always editors during the period of observation and the 31,007 researchers who are never editors during that period. The remaining 776 researchers, inevitably, are more homogeneous than the individuals in the complete sample, which undermines the discriminatory power of some of the variables. The 776 researchers are highly productive, with research interests close to the leading journal specialisms, almost all are (or were) affiliated with the department of one of the editors in charge (see tables 3 and 4). Taken together with identification now based only on within scientist time variation of the variables, the reduced heterogeneity explains the loss of relevance of productivity and field of expertise. All the network variables remain significant. In the case of the pooled logit estimates, disconnected scholars are less likely to sit on editorial boards and the researchers with a distance of four from an editor have the same chance of board membership as unconnected researchers. Researchers who are or have been a departmental colleague or a *protégé* of an editor in charge have a higher chance to serve as an editor.

Note that, for productivity, the estimated coefficient of *Maximum impact factor* variable maintains its significance, which suggests that a change to the quality of the researcher's output is more important than a change to the number of publications. The conditional probability of being an editor is positively associated, also, with the *Number of co-authors*. This could be interpreted as evidence that, among the 776 researchers who have been editors during their careers, those better able to recruit reviewers are preferred by editors in charge. *Affiliation to a top university* now has a negative and significant coefficient. In 99.8% of cases, this lower probability is balanced by a coefficient of *Same department* and the variation in the joint probability of being an editor is not statistically different from 0. Indeed, in the sample considered, if we employ fixed effects, we find only one researcher affiliated with a top university who was not, at some time, a departmental colleague of an editor. For these researchers, the higher probability of being editor, shown by the coefficient of the variable *Same department*, has to be interpreted jointly with the lower probability of being editor associated with *Affiliation to a top university.*

In terms of field-specific time trends, figure A2 of the online appendix contrasts the results of the fixed effects (solid line) and pooled (dashed line) logit models. The results of the pooled logit models are mostly within the 95% confidence interval of the fixed effects estimations (shaded area). These results confirm the absence of clear, field-specific time trends in both estimation approaches.

So far, we have investigated the probability of being an editor, but without distinguishing between principal and associate editors. Because these functions have different responsibilities, they might require different, skills. In order to assess whether and to what extent this affects the selection process, columns (3) and (4) of table 5 present the probability of being a principal editor and columns (5) and (6) show the probability of being an associate editor. When comparing the pooled logit models in columns (3) and (5) to the reference case (column (1)), we find no relevant differences. However, when we consider the fixed effects estimates in column (4) (principal editor), the social connection variables are mostly not significant in the regression related to principal editors, with the exception of *Mentor–protégé*, which retains its sign and significance. There are two possible explanations for this loss of significance. First, editors in charge might have more discretion than principal editors to appoint associate editors. In this case, social connections might not be associated with a higher probability of serving as principal editor. Second, the reduced sample of 285 researchers (3,408 observations) might lead to less precise estimations of the coefficients. Indeed, the signs of the non-significant estimated coefficients of the social connection variables for principal editors (column (4)) are coherent with the coefficients in column (2). For associate editors (column (6)), the results are consistent with those in column (2).

3.1. Robustness checks

We conducted three robustness checks. We applied different estimation methods and applied restrictions to our sample of 31,909 researchers we consider potential editors. In the third check, we conducted empirical analysis by types of homogenous journals.

3.1.1. Estimation methods

Given the binary nature the dependent variable *Editor*, we consider the logit models estimated in table 5 appropriate to describe the probability of being appointed editor. Logit models can also capture the potential heterogeneity of the effects of the variables on the likelihood of such an event. Online appendix table A3 reports the ordinary least square (OLS) estimates of three linear models exploring the probability of being appointed editor, principal editor or associate editor (online appendix table A3, columns 1, 2 and 3). The OLS estimates of the linear probability models are robust to distributional and heteroscedasticity assumptions. Also, the coefficients of the variables entering the model linearly can be interpreted directly as the average marginal effects, at the cost of imposing that such effects do not depend on the interplay with the other observable characteristics. To obtain a meaningful comparison of the results of the linear probability models to our benchmark case, columns 4, 5 and 6 of online appendix table A3 show the average marginal effects, calculated relying on the estimates of the pooled logit models reported in table 5. We find substantial coherence between the signs of the average marginal effects of the linear probability and logit models. Specifically, the linear probability model shows that researchers not connected to any editor in the co-authorship network are 5.7 percentage points less likely to become editors (2.2 for the logit model), and, among those with links to an editor, this probability reduces by 1.4 percentage points for each distance step from the editors in the co-authorship network (0.54 for the logit model). According to the logit model, researchers in the *Same department* as an editor are 2.6 percentage points, on average, more likely to become an editor, although the marginal effect loses statistical significance in the linear probability model. Researchers in a *Mentor–protégé* relationship with an editor in charge are 2.5 percentage points more likely to be appointed editors in the linear probability model and 1.6 percentage points more likely in the logit model.

In our benchmark estimates we consider pooled and the fixed effects logit models: the former omit the presence of time-invariant unobserved individual specific effects (α_i), the latter consider the probability of being an editor conditional on this unobserved component. There is a third possibility, which is to consider α_i as a random effect and estimate the marginal probability to be an editor. Omitting α_i could bias the pooled estimates; thus, we estimate a random effects logit model using maximum likelihood. Similar to the fixed effects logit, the potential advantages of the random effects model come at a cost: it requires strict exogeneity, correct specification of the entire distribution of all the random components and numerical integration to solve the estimation problem. Online appendix table A4 reports the estimates of the random effects logits for *Editors*, *Principal editors* and *Associate editors*. The signs of the estimated coefficients are comparable to those in columns (1), (3) and (5) of table 5 although, by construction, their size is not. Despite the likelihood ratio tests rejecting the hypotheses that individual random components can be omitted, if we focus on the social connection variables, we find substantial coherence between the pooled and random effects logit estimates: all the variables retain their significance and signs.

3.1.2. Potential editors: Sample restrictions

In this second set of robustness checks, we restrict the pool of potential editors to researchers publishing in top journals and with long careers. We first re-estimate the model for the subsample that includes only researchers with at least one top publication during their career. We define a top publication as an article published in one of seven top journals in economics and finance (i.e., in *American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics, Review of Economic Studies, Journal of*

Finance and *Journal of Financial Economics*).[7] Only 5,981 out the 31,909 researchers have at least one top publication, that is 18.7% of the whole sample. Interestingly, this percentage rises to 87.5% for the subsample of researchers with at least one editorship.

The second subsample used to test the robustness of our results includes only researchers with a career longer than 10 years, which reduces the sample to 14,082 economists.

Columns 1 and 3 of online appendix table A5 show that the results of the pooled logit models for these two subsamples are consistent with those reported in column (1) of table 5. For researchers with at least one top publication, the estimated coefficients of the social connection variables of the fixed effects logit are mostly in line with the baseline case (table 5, column (2)), with the exception of *Same department*, which loses its significance. For researchers with careers of more than 10 years, *Mentor–protégé* and *Not connected to editors* are not significant.

3.1.3. Journal types

In the third set of robustness checks we investigate whether our results are sensitive to the type of journal considered. Among the 17 leading journals, "house" and "top" journals may have different hiring processes from non-house and non-top journals. We followed Brogaard et al.'s (2014) definition of a "house" journal as a journal published by a university with a continuous presence of at least one editor from the hosting institution. According to this definition, we classified the following as house journals: *Journal of Political Economy, Journal of Financial Economics, Quarterly Journal of Economics, Review of Economics and Statistics, Journal of Human Resources* and *International Economic Review*. The remaining 11 (17 minus 6) were considered non-house. For top-seven journals, we considered the same seven journals used in the previous robustness check (section 3.1.2). classifying the remainder as non-topseven. We compared the estimates for house versus non-house journals and top versus non-top journals. House journals appointed 273 editors, non-house journals 764; the top-seven journals appointed 505 editors and the non-top-seven appointed 570.

In columns 1, 3, 5 and 7 of online appendix table A6, it can be seen that the results of the pooled logit models are consistent with those of the benchmark case (table 5).

When we include fixed effects and consider house journals the network variables lose their significance (a Wald test cannot reject the hypothesis that the coefficients jointly are equal to 0, p-value = 0.13). This is driven by the fact that almost all those scientists who have acted as editors for a house journal are connected to editors in the co-authorship network and were departmental colleagues of an editor. In the case of non-house journals, all the network

7 We refer to Card and DellaVigna (2013) for the selection of the five top journals in economics.

variables have the same sign and significance as those in column (2) of table 5. Because house journals hire their editors from within a restricted set of well-known colleagues while non-house journals consider a wider set of potential candidates, the fact that social connection variables are significant only for non-house journals may suggest that social connections are used mainly for information gathering purposes.

When we consider top-seven versus non-top-seven, social connections do matter. For top-seven, *Same department* has no discriminatory power because 97.5% of the researchers who have acted as an editor of these journals at least once are or were at some time departmental colleagues of an editor in charge. In the case of the non-top-seven, we cannot reject the hypothesis that the parameters of the variables *Not connected to editors* and *Minimum distance from editors* jointly are equal to 0. We interpret this as the evidence that the timing of the social connection matters. Recent social links in the co-authorship network (proxied by *Not connected to editors* and *Minimum distance from editors* calculated in $t-1$, $t-2$ and $t-3$) are valued more by top-seven journals, while professional relationships over the researcher's entire career proxied by *Same department* and *Mentor–protégé* variables, are valued more by non-top-seven journals.

4. Conclusions

This paper investigated the selection mechanisms used for the appointment of editors for 17 leading economics journals using publication data for 31,909 economists active between 1997 and 2009. The data allowed us to reconstruct researchers' scientific careers and their social network connections with editors in charge. We expected curriculum vitae, past productivity, potential capacity to recruit reviewers and field of expertise to be relevant to appointment to a journal editorial board. Our results confirm that the quality and quantity of scientific production are fundamental drivers of the probability of editorship.

We found also that social connections matter. Ceteris paribus, conditional on the unobserved time-invariant characteristics of the researchers, those connected to editors in the coauthorship network are more likely to be appointed editors; researchers at a distance of four from an editor have the same chance as those with no connections and researchers who were departmental colleagues or *protégés* of an editor have a higher chance of editorship.

Our results are qualitatively robust to changes in the model specification, refinements to the pool of eligible researchers and the set of editorial boards considered. It is only in the fixed effects estimates related to house journals, when restricting the pool of potential editors to a homogeneous group of economists, that the social connection variables are not jointly significant.

This paper provides more systematic evidence on how the scientist's productivity, research field and links to the editors in charge determine the composition of the editorial board in leading economics journals. Our results complement the available anecdotal evidence on the process of editors' hiring that could be found in periodic editors' reports or in the meeting minutes of the professional association managing committees responsible for publishing the journal. When recruiting a new editor, the editors in charge are always (at least) consulted; in some cases, search committees are organized to shortlist potential candidates (e.g., *Econometric Society* and *American Financial Association*).[8] Scientists working in the same research field typically replace editors after completion of their term of office[9] and editorial board interlocks are common. The conditions related to hiring in the case of economics journals can be summarized as "[b]oard members are selected to reflect the highest level of scholarship in the economics profession over the many different fields represented in the submissions, as well as for conscientiousness, judgment, and professional reliability as demonstrated in their refereeing for the journal" (Duflo 2018, page 641).

This paper contributes to the literature showing that social connections matter not only for recruitment of professors (Zinovyeva and Bague 2015), fund awarding (Ebadi and Schiffauerova 2015), association membership (Fisman et al. 2018) and publication decisions (Colussi 2018) but also for appointment to the editorial boards of leading journals. The effect of social connections on editor recruitment is expected to strengthen the ties among researchers in the same cluster, increase their publication scores, speed their career progress and facilitate access to funding. Although editorial board composition might not affect the quality of the published work (e.g., Brogaard et al. 2014), it may be a condition for the diffusion of innovative ideas within the discipline. According to the innovation diffusion literature (e.g., Cowan and Jonard 2004), diffusion of innovation is influenced greatly by the topology of individuals' networks. Because editors represent important nodes in the scientific network, editorial board composition will affect "when and how extensively an innovation diffuses through social networks" (Abrahamson and Rosenkopf 1997, page 290). If clusters of socially connected scientists act as barriers within a network, then the spread of new ideas will be limited.

We can only speculate about why, ceteris paribus, editors tend to appoint researchers that are closer to them in the co-authorship network, are department colleagues or are mentees. We can propose (at least) two competing explanations: on the one hand, it may be that the proximity between editors and researchers might reduce information asymmetries related to aspects not directly observable from the curriculum vitae (e.g, researcher's management skills); on the other hand it may be due to favouritism. Although the results

8 For the Econometric Society, see `www.econometricsociety.org/sites/default/files/documents/ecminutes_%202018-01_Philadelphia.pdf`; for the American Financial Association, see `www.afajof.org/wp-content/uploads/files/Editorial_Committee.pdf`.

9 See, for instance, "The Econometric Society annual reports report of the editors 2017–2018," *Econometrica* 87, 365–67 (2019). DOI:10.3982/ECTA871EDS.

for house versus non-house journals suggest that the prevailing explanation is reduced information asymmetry, further research is needed to exclude the possibility that favouritism plays a role in recruitment.

Supporting information

Supporting information is available in the online version of this article.

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