Economics Letters 154 (2017) 1–5

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Intergenerational field transitions in economics[☆]

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HIGHLIGHTS

- We documents trends of mobility across fields in economics.
- We find intergenerational field similarity is more prevalent in larger fields.
- Choosing different fields from advisors more likely to highly demanded fields.
- Positive relation between field productivity and the median level of co-authorship

ARTICLE INFO

Article history:
Received 28 July 2016
Received in revised form
21 January 2017
Accepted 2 February 2017
Available online 9 February 2017

JEL classification:
A1
A19
A23
J62

Keywords:
Intergenerational field mobility
Economics fields
Advisor–advisee relationships
Field productivity in economics

ABSTRACT

This note documents trends of socialization and intergenerational mobility across research networks (fields) in economics. Using data on advisor–advisee pairs, we find that intergenerational field similarity is more prevalent in larger and successful fields. We then show that researchers who do choose different fields than those of their advisors are more likely to switch to highly demanded fields in the job market. These results are consistent with the equilibrium of a model in which advisors' have concerns for their advisees' socialization and production outcomes. We also document a positive relation between field productivity and the median level of co-authorship at the field level, which is consistent with complementaries between socialization and productive efforts.

1. Introduction

In this note, we document trends in intergenerational field mobility in economics using the RePEc Genealogy project, which connects individual researchers with their Ph.D. advisors. Advisees choose their advisors matching their own interests and abilities (as well as other characteristics such as their academic standing and reputation for helpfulness, see e.g. Colander, 2005 and Barnes et al., 2010). Given that advisors should have a comparative advantage in transmitting knowledge in their own fields, we would generally expect a high degree of affinity between the academic subfields of advisors and advisees. We find that this is only partially true. We document that it is common for advisees to work in different fields from those of their advisors. This intergenerational divergence in research interests has some interesting features and varies across fields in meaningful ways. First, similarity in fields is common when the advisors work more on average in relatively large fields. Perhaps more importantly, the degree of field overlap between advisor and advisee is also strongly influenced by the productivity of the fields in which the advisor is working. Finally, advisees who

☆ Hauk acknowledges financial support from the Spanish Ministry of Economy and Competitiveness through the Severo Ochoa Program for Centers of Excellence in R&D (SEV-2015-0563) and through CICYT project number ECO2015-67171-P and from the government of Catalonia (2014 SGR 1064).

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http://dx.doi.org/10.1016/j.econlet.2017.02.001
0165-1765/

do not share their main field with their advisors are more likely to work in fields with a higher demand for new assistant professors. Taken together, these facts are consistent with the hypothesis that advisors care about supporting the career of their advisees even if that means a smaller influence of their own fields. An additional important finding is that larger fields (more productive and exhibiting more intergenerational field similarity) exhibit more cooperation among researchers, which is consistent with complementarities between socialization and productive efforts as in Cabrales et al. (2011) and Albornoz et al. (2016).

2. Data

We extracted data from three main sources. First, we used the RePEc Genealogy project to construct a dataset of advisors and advisees for all cohorts from 1980 to 2014. Second, we web scraped information on every research paper by the authors listed in the RePEc Genealogy project from the IDEAS-RePEc website. We then used the Journal of Economic Literature (JEL) classification codes on each research paper to associate an author with a field vector,[1] where we define a field as a one digit JEL classifier, and allow authors to work in multiple fields. Finally, we construct measures of coauthorship using data we web scraped from CollEc.[2] Our final dataset consists of 7950 researchers, 5990 advisor–advisee pairs and include information on all their papers, advisors, students and coauthors.

3. Patterns of intergenerational transmission of research topics

To explore the patterns of "intergenerational" field mobility, we first define a measure of research overlap between advisors and advisees, which resembles closely the index presented by Fafchamps et al. (2010). We use the one digit JEL field vector described above to construct a cosine similarity measure of field overlap between an advisor i and an advisee j,

$$\omega^{ij} = \frac{\sum_f x_f^i x_f^j}{\sqrt{\sum_f (x_f^i)^2 \sum_f (x_f^j)^2}}$$

where x_f^i is the proportion of 1 digit JEL field mentions for author i that correspond to the JEL field f. Note that this is a continuous measure that ranges from 0 (if i and j do not work on any paper in the same field) to 1 (if i and j wrote in exactly the same fields and in exactly the same proportion). In Table 1 we can see that the average field overlap between advisors and advisees is positive and significantly greater than zero at a 1% level (one-tailed t-test). We then compare this to the average field overlap between two authors, calculated by taking a random sample of one million author pairs and calculating the average measure of cosine similarity for this random selection.[3] As can be seen in Table 1,

Table 1
Average field similarity.

Variable	Mean	Std. Dev.	N
Advisor–advisee ω^{ij}	0.443***	0.187	5990
Random sample ω^{ij}	0.295	0.251	1 million

Summary statistics for advisor–advisee ω^{ij} and population ω^{ij} (estimated with a random sample of 1 million author pairs). A one-tailed t-test was performed on both means.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 2
Field similarity, field size and demand.

	Field overlap (ω^{ij})	
	(1)	(2)
Weighted size (s_i)	0.073	
	(0.005)***	
Weighted demand (d_i)		0.655
		(0.095)***
Constant	0.186	0.386
	(0.016)***	(0.008)***
R^2	0.05	0.01
N	5990	5990

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

advisor–advisee pairs are clearly more similar in terms of field choices than the average population. This is probably capturing the fact that students often select advisors working in the fields that they are interested in, and therefore are relatively biased towards choosing the same fields.[4] However, the main point of interest in this paper is the fact that we do observe that the similarities between advisors and advisees are low and, as we show below, they vary in a meaningful way across fields.

We then calculate for each advisor a measure of "weighted average field size" as

$$s_i = \sum_f x_f^i S_f$$

where S_f is measured as the number of authors with at least one article in field f:

$$S_f = \sum_i I_{x_f^i > 0}.$$

With these two measures, we can estimate the relationship between the advisor–advisee cosine similarity measure of field overlap and the weighted average field size of the advisor. Column 1 in Table 2 shows that there is a positive and significant relation between the advisor's weighted average field size[5] and the level of field similarity between advisors and advisees. This observation leads to:

Empirical Observation 1. *Intergenerational field mobility is less likely to occur when advisors work relatively more in larger fields.*

A natural concern with Empirical Observation 1 is whether it is driven by self-selection into fields by ability. In unreported analysis (available upon request), we observe that there is no correlation

1 More specifically, we conducted the analysis as follows: we added up for each author all the JEL identifiers at the uppermost level (a single letter without numbers) for every paper she had registered in IDEAS. Then, for every individual author, we constructed a vector with the sum of all of the JEL information contained in her papers, divided by field. For example, if the author has three papers registered in IDEAS classified as A1, B2 and B31 according to the JEL, a second paper classified as B4 and B21, and the third getting C1 and A as classification, then we obtained the following vector of JEL fields: (2, 2, 1, 0, …, 0), because she has 2 papers corresponding to A category, two papers in field B and another paper classified as C.

2 A RePEc service of rankings by co-authorship centrality for authors registered in the RePEc Author Service.

3 We also tried selecting a sample of 100,000 and two million pairs and the results were identical up to the first 6 digits.

4 In an alternative analysis, we assign a main field to each author (the one digit JEL code with the largest value in the field vector) and show that advisees tend to be biased towards working in the same main field as their advisor, relative to our general sample of authors. These results are available upon request.

5 This measure of weighted size was then divided by 1000 when we ran the regressions, so as to produce a more legible coefficient.

between field size and the share of authors listed in the top 10% and top 5% IDEAS-RePEc average ranking of authors for each field,[6] which we will use as a measure of average "quality" or productivity at the field level. If the probability of being a top author was correlated with unobserved ability, then this finding would suggest that selection is hardly a big issue. We can further mitigate the concern about selection by ability by running the same regressions supporting Empirical Observation 1, but restricting the sample of advisees to top 5% and 10% authors according to the IDEAS ranking. In an unreported analysis, we obtain similar results, which reassures us that self-selection by ability is not a main driver of our results.

Another potential source of concern stems from the fact that each JEL classification at the letter level has a different number of sub-categories. If authors were in fact working in fields defined at a more specific level (for example, at the 3 digit JEL code), and if more popular fields (defined at the 1 digit JEL level) were also fields with more sub-categories (at the 3 digit level), then we might be observing more similarity in more popular fields simply because they also have more sub-categories, and therefore we would be missing advisees changing their research fields but appearing still in the same 1 digit field category. We can address this concern by controlling for the number of 3 digit JEL categories in each 1 digit JEL field, at a field level regression. Since our measure of similarity is a continuous variable weighting all the fields at the author level, it is easier to tackle this potential bias by (i) attributing each author the field for which she/he has the largest number of publications, (ii) estimating the probability for an advisee working on a field j conditional on her/his advisor working on $j (H_f)$, and (iii) running regressions of that probability on the unconditional probability of this advisee working on field j (w_f) with controls for the number of sub-fields per field. Based on this estimation, we observe a positive association between H and w, which is another way to substantiate Empirical Observation 1 but controlling for the number of sub-fields per field. Furthermore, we find that the correlation between field size (number of authors attributed to the field) and the number of sub-categories by 1 digit JEL field, which turns out to be low and insignificant. Based on these results (available upon request), we can fairly state that our results are not mechanically generated by differences in the number of sub-categories across fields.

To infer whether intergenerational field mobility is related to the appeal of the field, we need a measure of profitability. As a proxy, we use a measure of success in the Ph.D. labor market for each field based on the *Survey of the Labor Market for New Ph.D. Hires in Economics* published by the Center for Business and Economic Research at the University of Arkansas. This survey collects information on over 200 organizations, including the demand and supply of new Ph.Ds by field of specialization, at the one-digit JEL identifier. We take the total demand for new Ph.Ds between 2009 and 2012 by field as our measure of appeal at the field level. We then construct a measure of weighted demand for each advisor as the weighted average demand for new Ph.Ds in the fields in which the advisor is active,

$$d_i = \sum_f x_f^i D_f$$

where D_f is the aggregated demand from 2009 to 2012 for new assistant professors in field f. The second column of Table 2 shows the coefficients resulting from the regression of w^{ij} on d_i for all advisor–advisee pairs. From this regression, we can clearly infer a positive relationship between the degree of field similarity between the advisor and the advisee, and the degree in which the advisor works in more demanded fields. We can therefore state,

[6] This measure is more thoroughly explained in the following section.

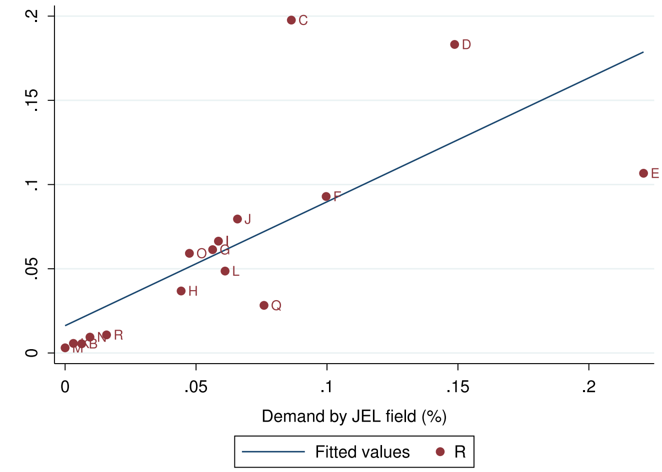

Fig. 1. Relationship between receptiveness and the proportion of demand by field.

Empirical Observation 2. *Intergenerational field mobility is less likely to occur when advisors work relatively more in fields with a larger demand for new Ph.D. Assistant Professors.*

The two previous observations imply that field mobility between advisor and advisee (understood as a low field similarity measure) seems to be negatively correlated with both the size and the demand of the fields in which the advisor is working. In order to also say something about what fields are being chosen by these advisees who are farther apart from their advisors, we use a discrete version of the similarity measure. We define for each author in our dataset their main field as the field for which her field vector has the largest value.[7] We can then calculate a measure of "receptiveness" by field as follows: we take all the advisees with a different main field than their advisors, and then calculate the share of those advisees that are in each main field. In this manner we can see how many "switchers" are received by each field. In Fig. 1 we plot the relationship between "receptiveness" and the relative demand by field.[8] This relationship is clearly positive implying:

Empirical Observation 3. *The fields with higher demand in the market for new Ph.D. Assistant Professors are those that attract a higher proportion of researchers working in different fields than those of their advisors.*

Taken together, Empirical Observations 1–3 are consistent with the existence of advisors' concerns about the success and productivity of fields chosen by their advisees. We turn now to the question of whether more productive fields exhibit higher or lower levels of socialization.

4. Networking and productivity

In this section, we report evidence that connects productivity with authorship interactions. We construct our variable of coauthorship as follows: for each economist in our dataset, we counted the number of her/his coauthors, we then also estimated the median number of coauthors by JEL main fields (where main fields for each author were defined as in the previous section);

[7] If there are multiple fields with the maximum values, the author is assigned all those fields as her main fields.

[8] In this figure we exclude fields A, P and Z as main fields because each one represent less than 0.2% of the total sample, results hold true if these fields are included.

Table 3
Median number of coauthors by JEL field and Top 10% authors by field.

JEL field	Median coauthors	"Top author" Share (%)
Economic Thought and Methodology (B)	3.5	14
Mathematical and Quantitative Methods (C)	5	25
Microeconomics (D)	5	27
Macroeconomics and Monetary Economics (E)	6	36
International Economics (F)	7	34
Finance (G)	6	42
Public Economics (H)	7	35
Health, Education, and Welfare (I)	5	21
Labor and Demographic (J)	7	36
Law and Economics (K)	4	31
Industrial Organization (L)	6	27
Business Administration and Economics (M)	6	18
Economic History (N)	6	32
Economic Development, Technological Change, and Growth (O)	8	36
Agricultural Economics (Q)	9.5	35
Urban, Rural, Regional (R)	8.5	39

that is, the median number of coauthors amongst all the authors in each field.[9] Table 3 displays the median number of coauthors for each field (column 1). This measure ranges from 3.5 in Economic Thought and Methodology to 9.5 in Agricultural Economics. Finally, we construct a measure of productivity. IDEAS-RePEc generates a series of rankings by author, from which we selected the Average Rank Score.[10] For each author, we define whether she or he is a "top author" according to whether she or he is included in the Top 10% of the IDEAS-RePEc of authors.[11] Finally, we calculate the share of "top authors" for each JEL field as a measure of field productivity (Table 3, column 2).[12]

Based on Fig. 2, we examine whether there is a relationship between the median number of coauthors and the share of "top authors". Clearly, there is a positive association that we summarize as:

Empirical Observation 4. *More productive fields are characterized by higher levels of coauthorship.*

A potential bias in our results may emerge if field popularity varied over time, so that some fields have on average younger researchers than others. If career length were positively related to both coauthorship and to a researchers probability of being in the IDEAS top 10% ranking, then we would be facing a confounding factor. In order to address this concern, we run the regression shown in Fig. 2 but controlling for the average number of years from Ph.D. graduation for researchers in each field. Table 4 reports both the regression with and without controls. As can be seen, the association between our measure of productivity and coauthorship remains almost unaltered with the inclusion of controls. Interestingly, we observe that the mean years from Ph.D. graduation is in fact negatively correlated with the median number of coauthors, so that the relation between median coauthorship and field productivity would seem to be bias our results downwardly. This is consistent with results at the author level, where we find that coauthorship is in fact decreasing in years from graduation. Both results are probably due to an increasing trend in economics to produce coauthored papers.

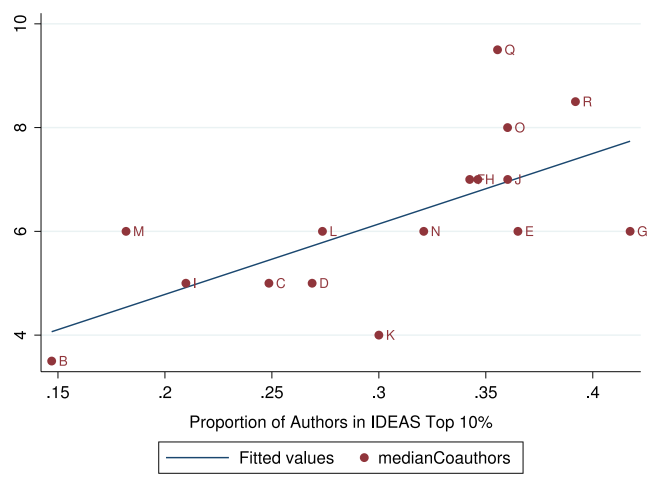

Fig. 2. Association between the median number of coauthors and the proportion of authors in the Top 10% in IDEAS ranking.

Table 4
Association between median number of coauthors and proportion of authors in IDEAS Top 10% ranking, with and without controlling for mean age by field.

	Median number of coauthors	
Top 10	12.786	13.610
	(2.722)***	(2.293)***
Mean years from graduation		−0.191
		(0.092)*
Constant	2.473	5.398
	(0.915)**	(1.684)***
R^2	0.46	0.56
N	18	18

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

5. Concluding remarks

This note has documented trends of socialization and intergenerational mobility within research fields in economics. The results on intergenerational field mobility could reflect that advisors might encourage and help their advisees to invest in the more profitable fields; a fact that is interesting in its own right that we inter-

[9] The median instead of the mean was used in order to mitigate the concern that sub-fields are highly influenced by some authors who are clearly outliers in the less popular fields.

[10] This score is determined by taking a harmonic mean of the ranks in each method, except the first one (number of works), the best, and the worst rank.

[11] We also use a more strict definition of "top author" using the Top 5% threshold.

[12] Note that our data is biased towards "top researchers" since we are using a subsection of all authors in IDEAS, because we are only considering authors who are also listed in CollEC and RePEc Genealogy. In almost all the fields, more than 10% of the researchers in our dataset are considered a "top researcher". As unreported robustness checks (available upon request), we use a measure of field productivity based on the share of published papers in top five Journals (American Economic Review (AER), Econometrica (EMA), the Journal of Political Economy (JPE), the Quarterly Journal of Economics (QJE), and the Review of Economic Studies (RES)) for each field, which was developed by Card and Della Vigna (2013).

pret as reflecting advisors' concerns about their advisees' socialization and production fields.

When interpreting coauthorship as an observable consequence of socialization, this empirical observation can be related to socialization in networks more generally. Our observation is consistent with the model prediction in Albornoz et al. (2016) where more productive networks are characterized by more socialization. It is also consistent with the empirical observations documented in Currarini et al. (2009) that individuals belonging to larger groups have more friendship connections *per capita*. The result nicely connects to a recent literature that has taken into account network effects in economic research. Ductor (2015) has shown that greater collaboration leads to higher academic productivity. Medoff (2003) empirically evaluate the predictive power of several network characteristics on individual research outputs in economic research. The productivity of coauthors, closeness centrality, and the number of past coauthors are particularly relevant to infer young researchers future productivity. Finally, our findings emphasize the relevance of considering intergenerational concerns and network effects to evaluate the effect of socialization on academic performance.[13]

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13 For example, neglecting a network effect yields a negative association between co-authorship and academic output (Hollis, 2001; Ductor et al., 2014).