THE MOVER'S ADVANTAGE: THE SUPERIOR PERFORMANCE OF MIGRANT SCIENTISTS

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Abstract

Migrant scientists outperform domestic scientists. The result persists after instrumenting migration for reasons of work or study with migration in childhood to minimize the effect of selection. The results are consistent with theories of knowledge recombination and specialty matching.

Keywords: foreign-born scientists; high-skilled migration; scientist mobility; brain drain; migrant selection

JEL: J61; F22; J24; O15

1. Introduction

There is considerable discussion concerning the importance of designing national research systems and immigration policies that attract and nurture international talents (Van Noorden 2012, Shen 2013, Mahroum 2001). This policy debate is informed by a limited, albeit growing corpus of scholarly research aimed at assessing the contributions of high-skilled workers in the

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host country, especially in the area of science, innovation and entrepreneurship (P. Stephan 2012, 183-, Kerr, U.S. High-Skilled Immigration, Innovation, and Entrepreneurship: Empirical Approaches and Evidence 2013). Prior studies of inventors and entrepreneurs have shown quite consistently that migrants significantly contribute to technological inventions and patenting (Hunt and Gauthier-Loiselle 2010, Kerr and Lincoln 2010) and to the founding of new ventures (Hunt 2011), at least in the US. However, the evidence of positive differentials seems to be largely attributable to migrant preferences for training in technical and scientific subjects (Hunt and Gauthier-Loiselle 2010, Hunt 2011). With regard to the performance of migrant scientists, the evidence is scant and more mixed (see Section 2). To the best of the authors' knowledge, no prior study tries to disentangle the degree to which the superior performance is attributable to migrants being pre-selected among the best and brightest and/or to ex-post treatment that affects performance differentials. Our paper contributes to this knowledge gap and shows that migrant scientists outperform domestic scientists even after using instrumental variables to neutralize the effect of endogenous selection into migration related to ability.

2. Migrant quality before and after migration

Insights from the knowledge recombination theory suggest that mobility of people facilitates mobility of knowledge and more knowledge from distant sources is associated with greater idea generation and creative attainments (Hargadon e Sutton 1997, Fleming 2001). Because knowledge is largely tacit and embedded in individuals, migrant scientists can arguably be exceptionally productive because mobility places them in position of arbitrage, where they can exploit rich or unique knowledge sets (Saxenian 2005, Agrawal, et al. 2011). Mobility can also enhance productivity because of specialization. Jones (2008) maintains that the specialized skills owned by high-skilled human capital deploy their full value when surrounded by complementary specialty skills. Matching is especially relevant in the academic labor market where many areas of expertise require dedicated laboratories and special equipment that exists in a limited number of settings and productivity depends on having the opportunity to work jointly with a team (P. Stephan 2012).

Despite these arguments, we have inconclusive evidence that gains from migration exist in practice. Some researchers find productivity differentials between migrants and non-migrant scientists. Levin and Stephan (1999), for example, show that authors of exceptional contributions are disproportionately distributed among the foreign born and foreign educated in the United States. Borjas and Doran (2012) show that the Russian mathematicians who migrated to the US following the collapse of the Soviet Union were largely outperforming US mathematicians. Gaulé and Piacentini (forthcoming) investigate the productivity of Chinese Chemistry students in US PhD programs and find them to be more productive and to experience a more rapid surge in productivity over time than non-Chinese PhD students. In contrast, Hunter and colleagues (2009) find that UK highly-cited physicists who migrated to the US perform similarly to domestic-US physicists; their performance is also no different from that of those who stayed. Stuen, Mobarak and Maskus (2012) show that the supply of foreign students increases the productivity of related departments, but find that the marginal impact of foreign and domestic students is not statistically different in magnitude. Stephan and colleagues (2007) look at the patenting activity of faculty at US universities. The analysis, which controls for a number of things, finds no evidence that patenting is related to whether or not the faculty member is a US citizen. No and Walsh (2010) find that the patents of foreign-born inventors with a PhD education receive on average fewer citations, although their patents are equally likely to have been commercialized when compared to the inventions of domestic inventors. In sum, empirical analysis that investigates the performance of migrant scientists is inconclusive. The studies that confirm the existence of differentials in performance are also incapable of distinguishing correlation from causality because the effect of mobility is blurred by selection into migration (Roy 1951). Prior investigations are also disproportionally focused on the US, and on samples of top-performing scientists, rather than on more representative samples. Yet national policies promoting mobility often assume the experience will benefit all.

We contribute to this knowledge gap by providing new evidence on the existence and causes of superior performance of migrant scientist by using a large new set of survey data from the GlobSci project,[2] especially designed to investigate migration in science (Franzoni, Scellato e Stephan 2012). To account for the confounding effect of individual ability, we instrument migrant scientists by using migration during childhood.

3. Survey and data

We surveyed a panel of active researchers during the period February-June 2011. To build the panel we first constructed a stratified sample of journals in four scientific disciplines: Biology,

[2] http://www.nber.org/workinggroups/ipe/ipe_researchproject.html

Chemistry, Earth and Environmental Sciences, and Materials Science. For each sub-field of these disciplines, we randomly picked a selection of journals and obtained a sample of journals stratified by Impact Factor, containing approximately 30% of all outlets in the four fields. From the bibliographic record of all research papers published in these journals during 2009, we retrieved the email address of the first corresponding author on a randomly selected focal paper. We restricted the panel to authors based in the following 16 core countries: Australia, Belgium, Brazil, Canada, Denmark, France, Germany, India, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, United Kingdom, United States.[3] This procedure produced a final panel of 47,304 authors, uniquely tied to a focal paper. The records were organized in 16 country panels whose sizes reflect by construction the size of the country research-active population. The panels also reflect by construction the distribution in performance of the related population of research-active scientists because the probability that authors would be chosen in one or another quartile of Impact Factor is random and in general not correlated to their prior international experience.[4] Panelists were invited by email a maximum of three times to answer a web-based questionnaire. The survey was developed in English and translated into French, German, Italian, Japanese, Portuguese and Spanish. In total, we received 19,183 usable answers. The overall response rate is 40.6%; if considering only those who reached the final question, it is 35.6%.[5] This is a high response rate, compared to similar studies and does not account for undelivered emails that typically bias the response rate downwards (Walsh, Cohen, and Cho, 2007; Roach & Sauermann, 2010). We performed a series of tests to assess the degree to which the sample represents the population concerning the Impact Factor distribution. These are available online as additional material and show minimal evidence of bias (see Supplementary Information).[6]

For the purpose of this paper, we use only the 15,672 respondents who reported an academic affiliation. After dropping records with incomplete information or inconsistent reports of international mobility, we obtain a final sample of 14,299 observations. Country of origin of the respondent was determined by asking in which country the person was living at the age of 18; respondents indicated 124 different countries. We also ask if the respondent had ever moved

[3] We initially intended to include China and Korea, but effort to field the questionnaire in the two countries proved unsuccessful and were therefore abandoned.

[4] For example, an author with four publications, one in each quartile of Impact Factor, had an equal probability of being included in our panel with a very good, medium-high, medium-low or low Impact Factor focal article.

[5] The response rate varies by country, with a high is 69.0% for Italy, a low is 30.3% for Germany; 11 countries have a response rate of between 35.0% and 45.0%.

[6] For a comprehensive description of the sample and tests see also the supporting information provided in Franzoni, Scellato and Stephan (2012).

since age 18 for reasons of work or study and if they currently live in a country other than that of origin. In total we identify 3,160 scientists who are migrants at the time they took the questionnaire. By sample construction, country of affiliation at the time of the response is limited to one of the 16 core countries. Domestic scientists are identified as those currently studying or working in their country of origin. For both migrant and domestic scientists we also have information on country of birth and other relocations that occurred for study (MA, BA, PhD), postdoctoral training, work or visiting (of at least one year), plus control information on the individual and the focal article.

4. Performance of migrant scientists

Our measure of performance is the Impact Factor of the focal article. Figure 1 shows the distribution of domestic and migrant scientists in the sample, by quartiles of the Impact Factor. Quartiles have been computed separately for each field. It is apparent that the proportion of migrant scientists increases as we proceed from the bottom to the top quartile of the Impact Factor, going from 20.7% in the first quartile to 29.2% in the forth.

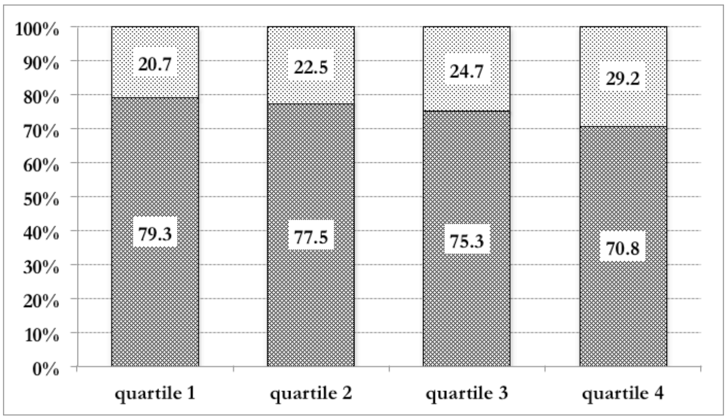
We investigate this further with multivariate analysis, comparing the relative performance of migrant and domestic scientists operating in 2009 in the same research system and fields net of the effect of potentially confounding factors. These include a set of individual characteristics: age, gender, status of trainee (PhD student), H-index of the country of origin[7] and a set of characteristics of the focal paper: number of co-authors, international coauthorship, newness of the research area. All models also control for field and country of current affiliation. Models 1-3 of Table 1 report the estimated correlation between the status of migrant and the logarithm of the Impact Factor. The coefficient of the variable *MIGRANT_SCIENTIST* is always positive and significant, confirming that migrant scientists exhibit superior performances. The coefficient of Model 1 corresponds to the estimated performance premium of the average migrant scientist compared to the average domestic scientist. This is +1.07, a moderate size Impact Factor premium.[8] In Model 2, we run the same specification but eliminate from the sample all domestic scientists who had a prior experience of mobility for reasons of study or work (i.e. had tertiary education or doctoral studies in a foreign country or had a former postdoc or employment

[7] H-Index by country and by subject category, computed for all publications in 1996-2010. Source: Scimago Journal and Country Rank. Retrieved from http://www.scimagojr.com on April 18, 2012.

[8] Summary statistics of Impact Factor: Mean=3.78; St.dev.=3.31; Median=2.90; Min=0; Max=31.25. Impact Factor=1.07 is a value equal or greater than the 6% of all Impact Factor values in the distribution.

experience in a foreign country) but have now returned. The marginal effect of the independent variable now expresses the Impact Factor performance premium of migrant scientists (+1.17) compared to the domestic scientists with no prior experience of mobility. We find a similar result in the estimate of Model 3, in which we use the full sample of migrant and domestic scientists, and control for prior international experiences of domestic scientists by including a variable that captures the h-index of the country in which the domestic scientists had prior international experience.[9] The corresponding marginal effect (+1.14 of the Impact Factor) is similar to that estimated in Model 2. Note that in all models *all* other regressors have the expected signs. Collectively, the results of Models 1-3 provide robust evidence that scientists who migrate for reasons of work or study perform in the host country at a higher level than domestic scientists with or without mobility experience.

Figure 1 Proportion of domestic and migrant scientists by quartiles of Impact Factor



Dark-grey=Domestic scientists; Light-grey=Migrant scientists. Quartiles computed by discipline. Proportions weighted by probability of response.

Observing evidence of the superior performance of migrant scientists is not sufficient for inferring causality, given that the correlation is blurred by positive selection into migration. Selection occurs because, assuming that earnings -or fellowships for study- are an increasing function of ability, only more capable scientists are offered opportunities that are sufficiently large to outbalance the cost of relocation (Borjas 1994, Grogger e Hanson 2011, Gibson e McKenzie 2012). Thus, the unobservable ability of individuals is correlated both to migration and to performance. This causes correlation of the regressor *MIGRANT_SCIENTIST* with the error

[9] This is an interaction variable of a dummy equal to 1 if the domestic scientist had a prior international experience and the H-index of the country of prior international experience (in thousands). Summary statistics of Domestic prior int. exp. X country h-index: Mean=0.28; St.dev.=0.46; Median=0; Min=0; Max=1.23

term, which leads to potentially biased and inconsistent estimates. In order to overcome this problem of endogeneity, we choose to instrument the variable *MIGRANT_SCIENTIST* with migration events that occurred during childhood (*CHILD_MIGRATION*). Scientists migrated during childhood are coded from the whole dataset as those reporting a country of birth different from the country of origin.[10] By construction, the latter is the country of residency at the time the respondent turned 18. Child migration is arguably not caused by individual performance (exogenous), because relocation events occurring before the age of 18 likely reflect parental decisions, rather than choices of the respondent. We expect mobility during childhood to be correlated to migration decisions in adult life, because prior experience of relocation makes one more open to relocation opportunities, more able to overcome cultural shocks, *et cetera* associated with mobility. It is important to acknowledge that the validity of the instrument depends on the assumption that migration in childhood occurs to both children of higher and lower ability parents and/or irrespective of family investment in education.

Columns 4 to 6 of Table 1 report the results of two-step feasible GMM estimates, in which *MIGRANT_SCIENTIST* is treated as endogenous and instrumented by *CHILD_MIGRATION*. The first-stage F-statistics ranges between 69.7 and 79.9, above the conventional threshold of 10 (Staiger and Stock 1997), confirming that the instrument is valid and the equation is correctly identified. Results of the Model 4 report the estimates of a specification analogous to that in Model 1. The coefficient is positive and significant at 90% confidence level, confirming that mobility boosts individual performance. The estimated Impact Factor performance premium amounts to +1.49 compared to the average domestic scientist. When we restrict the sample to exclude domestic scientists with prior experience of international mobility (Model 5), the Impact Factor performance premium for migrating scientists is estimated to be +1.53 compared to domestic scientists with no prior experience of international mobility and the coefficient is significant at the 95% level of significance. This result is further confirmed in Model 6, where we include the entire sample and control for prior international experience of the domestic scientists.

In summary, the models corroborate the predictions of the theory of knowledge recombination and specialty matching that migration enhances the performance of scientists, after controlling for the effect of selection into migration.

[10] There are 699 respondents reporting migration during childhood in our sample. Of these, 416 are currently in the same country (domestic) and 283 are currently migrant scientists in a different country. Correlation with *MIGRANT_SCIENTIST*=0.10***. Summary statistics of the dummy variable *CHILD_MIGRATION:* Mean=0.05; St.dev.=0.22.

Table 1 – Performance of migrant scientists

Dependent variable: Ln(Impact Factor)	(1) OLS	(2) OLS	(3) OLS	(4) IV⁺	(5) IV⁺	(6) IV⁺
MIGRANT_SCIENTIST	0.071 ***	0.154 ***	0.133 ***	0.396 *	0.428 **	0.371 *
	(0.014)	(0.015)	(0.014)	(0.217)	(0.176)	(0.208)
Domestic prior int. exp. X country h-index			0.140 ***			0.185 ***
			(0.009)			(0.040)
Age	0.012 ***	0.014 ***	0.010 ***	0.015 ***	0.015 ***	0.011 ***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Age^2	-0.000 ***	-0.000 ***	-0.000 ***	-0.000 ***	-0.000 ***	-0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.044 ***	-0.026 **	-0.038 ***	-0.048 ***	-0.026 **	-0.039 ***
	(0.009)	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)
D_Still in training	-0.083 ***	-0.042	-0.069 ***	-0.059 **	-0.010	-0.049
	(0.025)	(0.026)	(0.025)	(0.030)	(0.034)	(0.031)
H-Index country of origin	0.144 ***	0.214 ***	0.179 ***	0.476 **	0.485 ***	0.413 **
	(0.022)	(0.023)	(0.022)	(0.222)	(0.175)	(0.205)
D_emerging area of research	0.150 ***	0.150 ***	0.146 ***	0.145 ***	0.144 ***	0.142 ***
	(0.008)	(0.010)	(0.008)	(0.009)	(0.011)	(0.009)
D_Internationally-coauthored article	0.029 ***	0.011	0.022 **	0.011	-0.014	0.007
	(0.009)	(0.011)	(0.009)	(0.016)	(0.020)	(0.016)
Number of coauthors of focal article	0.038 ***	0.042 ***	0.038 ***	0.038 ***	0.043 ***	0.038 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.706 ***	0.507 ***	0.704 ***	0.434 ***	0.287 *	0.521 ***
	(0.082)	(0.095)	(0.081)	(0.199)	(0.171)	(0.179)
Current country of affiliation dummies	yes	yes	yes	yes	yes	yes
Field Dummies	yes	yes	yes	yes	yes	yes
Sample	All	Domestic. not-mobile; Migrants	All	All	Domestic not-mobile; Migrants	All
Observations	14,299	9,954	14,299	14,299	9,954	14,299
Adj. R-sq	0.201	0.229	0.214	0.169	0.204	0.198
Cragg-Donald F-stat.				69.74	93.74	79.90

*p≤.10;**p≤.05;***p≤0.01. Robust st. err. in parentheses. ⁺Two-step feasible GMM estimate. Instrumented: *MIGRANT_SCIENTIST*; Excluded instrument: *CHILD_MIGRATION*.

5. Discussion and conclusion

A question of considerable importance is whether mobile scientists outperform the non-mobile. To answer this important question, we employ a new rich survey designed specifically to study migration of scientists in four fields of science and 16 countries. Results confirm that migrants perform at a higher level than domestic scientists with or without prior experience of international mobility. Superior performance is potentially caused by gains from knowledge recombination and specialty matching subsequent to migration. However, because superior performance can also be caused by positive selection into migration, we instrument migration for reasons of work or study with migration in childhood, to mitigate the effect of selection. We find the superior performance of migrant scientists to persist, suggesting that migration is a likely cause of superior performance. This is consistent to predictions of the knowledge recombination (Saxenian 2005, Agrawal, et al. 2011) and specialty matching (Jones 2008) theories. We therefore interpret our finding as corroborating these theories, although it is important to note that alternative explanations of a superior ex-post performance of migrants also exist. For example, it is possible that, faced with a discriminating environment in the host country, migrants feel pressure to perform better than domestic scientists.

Regardless of interpretation, the result has at least two important implications for scholars and policy makers. First, it confirms the validity of policies aimed at facilitating increased brain exchange across countries. Such policies include easier immigration procedures for high-skilled human capital (Shen 2013), and policies aimed at harmonizing the international job market for research (Franzoni, Scellato and Stephan 2011). Second, our findings that the positive effects of migration persist having controlled for selection, suggest that brain migration is not a zero-sum gain, in the sense that the benefits that accrue to the destination country do not necessarily come at the expense of the sending country, and that there are conversely positive externalities to be gained by promoting mobile scientists to work with domestic scientists.

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SUPPLEMENTARY INFORMATION (ONLINE APPENDIX)

Table 2 reports the number of records in each country panel, the total number of answers, further divided into answers from respondents that reached the final question (complete) and from respondents that did not reach the final question (dropout). It also reports the total response rate, computed as the share of the total answers on the panel and the complete response rate, as the share of the complete answers on the panel.

Table 2 Response rate by country[11]

	PANELS	TOTAL ANSWERS	OF WHICH COMPLETE	OF WHICH DROPOUT	TOTAL RESPONSE RATE	COMPLETE RESPONSE RATE
Australia	1,571	676	610	66	43.0%	38.8%
Belgium	706	302	244	58	42.8%	34.6%
Brazil	1,537	762	692	70	49.6%	45.0%
Canada	2,455	1,020	897	123	41.5%	36.5%
Denmark	513	227	208	19	44.2%	40.5%
France	3,839	1,618	1,367	251	42.1%	35.6%
Germany	4,380	1,326	1,147	179	30.3%	26.2%
India	1,380	627	484	143	45.4%	35.1%
Italy	2,779	1,917	1,759	158	69.0%	63.3%
Japan	5,250	1,860	1,678	182	35.4%	32.0%
Netherlands	1,036	391	345	46	37.7%	33.3%
Spain	2,303	1,228	1,080	148	53.3%	46.9%
Sweden	882	353	301	52	40.0%	34.1%
Switzerland	919	356	320	36	38.7%	34.8%
UK	3,695	1,355	1,183	172	36.7%	32.0%
U.S.	14,059	5,165	4,512	653	36.7%	32.1%
Total	**47,304**	**19,183**	**16,827**	**2,356**	**40.6%**	**35.6%**

[11] Respondents were both academics and non-academics. In this paper we analyse the 15421 answers from academics.

Representativeness of sample

We performed three different checks concerning potential differences in scientific impact, as assessed by the journal impact factor of source articles. A final check is performed on a self-reported assessment of article representativeness.

Table 3 Two-groups comparisons of Impact Factor in 16 countries by 4 subject categories. T-Tests. Hypothesized difference (respondents – non-respondents)=0

COUNTRY	**DIFFERENCE (RESPONDENTS - NON-RESPONDENTS)**							
	Biology		**Chemistry**		**Earth & Environment**		**Materials Science**	
	mean	st.err.	mean	st.err	mean	st.err	mean	st.err
Australia	0.036	0.357	-0.350	0.211	-0.090	0.127	0.316	0.341
Belgium	-0.611	0.563	0.357	0.429	0.089	0.265	0.745	0.531
Brazil	0.224	0.115	0.092	0.103	-0.290	0.198	0.381	0.188*
Canada	0.535	0.320	0.287	0.182	-0.180	0.116	-0.118	0.280
Denmark	0.465	0.640	-0.213	0.357	-0.439	0.261	0.286	0.681
France	0.024	0.268	0.164	0.136	-0.085	0.107	0.065	0.149
Germany	0.185	0.320	0.135	0.180	0.172	0.108	-0.059	0.197
India	-0.196	0.186	0.060	0.133	0.073	0.180	-0.066	0.124
Italy	0.674	0.270*	0.080	0.142	-0.026	0.114	-0.067	0.217
Japan	-0.387	0.250	-0.045	0.122	0.229	0.120	0.040	0.125
Netherlands	0.366	0.369	0.009	0.402	0.185	0.194	-0.773	0.540
Spain	0.493	0.254	0.099	0.134	0.043	0.127	-0.433	0.188*
Sweden	-0.415	0.544	0.632	0.434	-0.035	0.233	0.107	0.486
Switzerland	0.452	0.662	-0.372	0.390	0.131	0.181	0.380	0.589
UK	0.589	0.283*	0.164	0.184	0.065	0.110	0.188	0.250
USA	1.111	0.187*	0.584	0.094*	-0.043	0.058	0.319	0.161*
OVERALL+	**0.705**	**0.088***	**0.315**	**0.046***	**0.041**	**0.032**	**0.209**	**0.062***

+Weighted by probability. *p<0.5

First, we asses potential bias due to unit-non response by comparing the Impact Factor of respondents in each of four subject categories and each of 16 countries, against those of non-respondents (Table 3). Results indicate modest potential biases in the samples from Brazil (Materials science) Italy (Biology), Spain (Materials Science) and US (Biology, Chemistry and Materials Science)[12]. Except for Spain, biases are in the direction of over-representing authors with higher-impact papers.

Second, we compare the impact factor of early respondents against those of late respondents. Late respondents are characterized as those who completed the questionnaire during the third (final) round, as opposed to those who completed the questionnaire during the first and second rounds (Table 4). This screening is useful to assess the potential existence of biases due to item

12 Note that only that Bonferroni-adjusted p-value would indicate significant differences and only for the US sample.

non-response, but can also be helpful to assess the severity of bias for unit-non-response, if we expect that late-respondents would be more similar to non-respondents (or to those who would have responded if we had solicited the questionnaire one more round). T-test comparisons highlight modest biases concerning the Japan sample in Biology, and the Sweden and US samples in Earth & Environmental sciences, where authors of higher-impact contributions were disproportionately distributed among late respondents[13].

Table 4 Two-groups comparisons of Impact Factor in 16 countries by 4 subject categories. T-Tests. Hypothesized difference (early respondents – late respondents)=0

COUNTRY	DIFFERENCE IMPACT FACTOR (EARLY - LATE)							
	Biology		Chemistry		Earth & Environment		Materials Science	
	mean	st.err	mean	st.err	mean	st.err	mean	st.err
Australia	0.368	0.720	-0.206	0.429	-0.009	0.390	-0.754	0.692
Belgium	0.912	1.457	1.385	0.982	0.612	0.469	-1.007	0.734
Brazil	-0.427	0.240	0.316	0.218	0.093	0.402	-0.098	0.153
Canada	-0.986	0.585	-0.438	0.363	0.031	0.269	0.098	0.664
Denmark	1.820	1.524	-0.260	0.794	0.557	0.581	0.340	1.395
France	0.439	0.575	0.028	0.304	-0.137	0.264	-0.666	0.363
Germany	-0.576	0.721	-0.318	0.433	0.065	0.290	0.208	0.587
India	-0.238	0.413	-0.057	0.276	-0.049	0.391	0.338	0.288
Italy	-0.055	0.400	0.248	0.243	-0.426	0.233	-0.036	0.419
Japan	-2.060	0.856*	-0.212	0.365	-0.285	0.371	0.260	0.377
Netherlands	0.307	0.663	-1.503	0.980	-0.667	0.406	0.607	1.081
Spain	-1.431	0.473	-0.072	0.314	0.338	0.311	0.139	0.418
Sweden	-0.600	1.278	1.803	0.960	-1.525	0.727*	-0.703	1.232
Switzerland	-1.597	1.331	1.026	0.929	0.647	0.455	1.435	1.428
UK	0.099	0.612	0.334	0.473	0.374	0.244	0.374	0.474
USA	-0.167	0.369	-0.089	0.190	-0.257	0.123*	0.445	0.327
OVERALL[+]	**-0.414**	**0.120**	**-0.080**	**0.102**	**-0.145**	**0.075**	**0.061**	**0.133**

[+]Weighted by probability. *p<0.5

Third, we compare respondents who took the entire questionnaire against respondents who dropped-out before completing the survey (

[13] Note that no difference would be significant if Bonferroni-adjusted p-values were used.

Table 5). This check is meant to assess potential biases due to item-non-response, for example caused by the fact that certain incomplete observations (like country of origin) made the response not-usable for our purposes. Moderate biases are highlighted for Belgium (biology), Germany and India (Chemistry), Japan and US (Earth & Environment), where authors of higher-impact papers were comparatively more likely to complete the questionnaire[14].

[14] Note that Bonferroni-adjusted p-values would only indicate as significant the differences between samples in the Belgian sample in Biology.

Table 5 Two-group comparisons of Impact Factor in 16 countries by 4 subject categories. T-Tests. Hypothesized difference (complete respondents – dropped-out respondents)=0

COUNTRY	DIFFERENCE IMPACT FACTOR (COMPLETE - DROPPED-OUT)							
	Biology		Chemistry		Earth & Environment		Materials Science	
	mean	st.err	mean	st.err	mean	st.err	mean	st.err
Australia	-0.926	0.934	-0.213	0.421	-0.245	0.428	0.693	0.732
Belgium	-3.043	1.025*	0.878	0.959	-0.044	0.404	1.085	0.846
Brazil	0.026	0.274	-0.157	0.283	-0.630	0.623	0.214	0.356
Canada	0.036	0.712	-0.167	0.404	-0.294	0.273	-0.152	0.633
Denmark	-2.309	1.549	-0.656	0.962	0.355	0.939	1.492	1.487
France	-0.128	0.574	0.354	0.251	-0.015	0.235	0.178	0.298
Germany	-0.384	0.709	0.904	0.407*	0.323	0.271	-0.338	0.482
India	0.539	0.335	0.519	0.209*	-0.261	0.271	0.046	0.206
Italy	0.263	0.528	0.068	0.271	0.081	0.268	-0.124	0.433
Japan	1.090	0.711	-0.246	0.301	0.630	0.307*	0.040	0.335
Netherlands	1.154	0.794	1.715	1.215	0.431	0.426	-1.746	1.270
Spain	0.930	0.524	0.388	0.266	0.136	0.243	0.023	0.439
Sweden	0.808	1.313	-0.267	0.924	-0.565	0.478	-0.002	0.782
Switzerland	-0.434	1.581	0.876	1.104	0.086	0.408	1.013	1.788
UK	0.120	0.629	-0.101	0.457	-0.263	0.252	0.531	0.533
USA	0.663	0.438	0.322	0.221	0.302	0.132*	-0.069	0.333
OVERALL[+]	**0.324**	**0.203**	**0.373**	**0.095***	**0.117**	**0.072**	**0.081**	**0.131**

[+]Weighted by probability. *p<0.5

In sum, the controls performed on the set of information known ex-ante point to moderate evidence of bias. If biases exist, they seem to be more likely in the direction of slightly over-sampling correspondent authors of higher quality papers.