Research careers in Europe: New evidence from the Doc-Track database

Alberto Corsini [1], Johannes Koenig [2,3], Burcu Özgun [2,4], Andriy Romanyuk [5,6], Guido Buenstorf [2], Francesco Lissoni [5,7], Ernest Miguelez [5,8], Michele Pezzoni [9] & Catalina Martinez [1]

[1] Institute of Public Goods and Policies, IPP-CSIC – Spanish National Research Council
[2] INCHER and Institute of Economics – University of Kassel ; [3] IAB – Institute for Employment Research, Saarbruecken
[4] Department of Human Geography and Spatial Planning, Utrecht University
[5] BSE UMR CNRS 6060 INRAE UMR 1441 – Université de Bordeaux ; [6] Department of Economics – Universita` dell'Insubria
[7] Department of Economic Policy – Universita` Cattolica del Sacro Cuore ; [8] AQR-IREA – University of Barcelona
[9] GREDEG UMR CNRS 7321 – Université Côte d'Azur

This draft: November 24th, 2025 (please do not quote nor cite)

Abstract

We present early evidence from Doc-Track, a new cross-country and longitudinal database on doctoral graduates' research careers in science, technology, engineering, mathematics and medicine (STEMM). Based on all dissertations discussed from 2000 to 2020 and archived in electronic form in Germany, France, Spain, the Netherlands, and Austria, we first identify all STEMM graduates in the same period and retrieve their publications during and after their doctoral spell. Based on this, we confirm results from a number of country-specific studies on the declining share of graduates undertaking a career in research – as measured by scientific authorship - but also find significant cross-country differences in both levels and trends. The declining trend as well as the observed cross-country differences become clearer after controlling for a number of observables, both at the individual and the country level, which suggests they are due to structural cross-country differences in the nature of doctoral training and/or the labour market. When distinguishing between academic and non-academic publications, we find that – conditional on publishing after graduating – the probability to do so outside academia is increasing, albeit being very low. Post-doctoral mobility is also increasing, as measured by the probability to publish with a different affiliation and in a different country than those of the PhD period. This is coherent with both the increasing integration of the European Research Area and the increasing share of international students. The Doc-Track data mining and record linkage methods are scalable and transferable to other countries, which will allow us to create a permanent observatory on doctoral graduates' careers.

JEL classification: I23, J24, O57

Keywords: STEMM; Doctoral training; EDT; Publications; Research careers; EU; Doc-Track

Acknowledgements: This work results from the research project "DOC-TRACK: STEM Doctoral Graduates and Inventive Activities in European Countries" funded by the European Patent Office Academic Research Program (EPO-ARP 2021). Use of publication data from Scopus was enabled by the German Competence Network for Bibliometrics funded by Bundesministerium für Bildung und Forschung (BMBF), grant number 16WIK2101A. We also acknowledge funding from the Deutsche Forschungsgemeinschaft (Germany) under grant BU 2454/8-1 (FOR 5234), from the BMBF under grant 16RBM1011, and from the Spanish national research project INNDOC AEI PID2023-149135NB-IOO. We thank the Spanish Ministry of Science, Innovation and Universities, ABES, DNB, DANS and ONB for access to, respectively, the Spanish, French, German, Dutch and Austrian EDT data. Pauline Menu, Carla Fournier, Luca Codecasa, Francesca Ammerata, Bradley Butcher, Aman Araissi, Valentine Petzold, Baptiste Comby, Lucien Boucart, Samuel Desneulin and Clovis Sourisse provided excellent research assistance. We thank participants at the STI2024 Conference held in Berlin for their comments. Research results and views included in the paper are only those of the authors and do not necessarily represent the views of funding institutions.

1. Introduction

Doctoral training has become the worldwide dominant model for early career researchers who aspire to pursue academic careers. The PhD degree attests the doctoral candidates' ability to perform independent research after several years of doctoral education, during which they acquire knowledge at the frontier of science as well as research skills. Moreover, their scientific contributions have become essential to their laboratories' research production (Corsini et al., 2022; Larivière, 2012; Shibayama, 2022).

A growing body of literature investigates various aspects of doctoral education, with special emphasis on its private and public economic value. A dominant theme is the observation that the number of PhD degrees awarded has increased significantly over time in most countries with a strong university system, while the share of graduates securing an academic position has declined (OECD, 2021; Sarrico, 2022). These trends have given rise to various concerns, namely: that doctoral students and young graduates, especially foreign ones, are used as temporary workforce in place of permanent laboratory technicians or tenure-track faculty (Stephan and Ma, 2005; Stephan, 2012 and 2013); that imbalances between the increasing supply of graduates and a limited availability of faculty positions may cut too many research careers short (Milojevic et al., 2018; Kwon, 2025); and that the doctoral training and/or the years spent on postdoc contracts may not result in higher productivity and wages when ultimately moving to non-academic jobs (Koenig, 2022 and 2024; Marini and Henseke, 2023). More nuanced views of the career perspective of doctoral holders, especially in science, technology, engineering, mathematics and medicine (STEMM), point out that many of those who do not undertake an academic career decide so early on during their studies and are less attracted to it from the start (Sauermann and Roach, 2012; Balsmeier and Pellens, 2014; Roach and Sauermann, 2017); and that many STEMM graduates may profit of an increasing offer of research-oriented jobs in the business sector (Buenstorf et al., 2023; Martinez and Parlane, 2023). This, in turn, raises the question of the adequacy of doctoral training models for preparing to non-academic jobs and even non-research ones. Two related themes concern the individual determinants of success in establishing a research career, whether in academic or outside it, with the quality of mentorship and gender having been proven to play a significant role (Corsini et al., 2022), alongside with the prestige and visibility of the degree-granting institution (Hancock 2023; Buenstorf et al., 2025).

The data mobilized by the literature vary considerably, each source presenting its own set of trade-offs. Survey data, collected through questionnaires administered to doctoral students during and/or after graduation, provide detailed information on individual biographical data, motivations, and subsequent employment (in or out the academia, research-related or not). However, they often lack a longitudinal dimension. With the exception of the NSF Survey of Earned Doctorates, an annual census of individuals earning research doctorates in the United States (Okrent and Burke, 2021; Opsomer et al., 2021), they are generally occasional or highly irregular over time; moreover, they do not follow the same individuals over time and, if they do, they cover a limited time period. They are generally conducted on a national basis and do not track the graduates who go abroad, the main exception being the Careers of Doctorate Holders survey,

conducted jointly by the OECD, UNESCO and Eurostat, but only in 2009 (Auriol, 2010; and Auriol et al., 2013). This prevents international comparisons and a detailed analysis of mobility patterns, a limitation whose importance increases with the rise in number of international graduate students (Ganguli and MacGarvie, 2025). Survey data also come - more often than not - in anonymized form, which prevents data linkage to other information sources.

The main alternative to surveys consists in combining archival records on doctoral graduates to other information sources, such a bibliographic databases or social security and other employer-employee databases as well as social media records. In the first case, the main goal is to find out which graduates keep publishing after their graduation and for how long, with the publication activity used a proxy measure for an employment in research and the author affiliation used for establishing the graduate's employer and location over time, conditional on publishing. This strategy is limited to the extent that it assumes that research leads inevitably to publishing (a more appropriate assumption in academia than outside it) and does not allow to find out what jobs the graduates who stop publishing take up and where (for a discussion, see Hanlon, 2019; and Milojevic et al., 2019). At the same time, it has the advantage of allowing for a long-term monitoring of active researchers, including of their mobility and of the quality of their research, especially within the academia. In the second case, information can be retrieved on non-academic careers but access to sensitive data such as employment records is very unequal across countries, which limits the potential for international comparisons. In both cases, the increasing availability of theses and dissertations in electronic form (EDTs) provides the possibility to go back in time and consider at once many cohorts of graduates as well as to update whatever data are collected for the graduation cohorts to come. So far, this possibility has been exploited for country-level study (Geuna and Shibayama, 2015, on Japan; Kahn and MacGarvie, 2016, on the US; Corsini et al., 2022, on France; Carriero et al., 2024, on Italy). The Doc-Track project's main goal is to exploit it in an international perspective.

To do so, it relies on matching information extracted from EDTs to a variety of bibliographic resources. In this paper, we present early results for 21 cohorts of 784,727 graduates (from 2000 to –2020) in five European countries (Germany, France, Spain, Netherlands, and Austria), matched to more than 35 million scientific authors from the Elsevier Scopus database for the period 1996-2022.

Based on these data, we provide cross-country and longitudinal evidence on the graduates' research careers – as defined by their publication activity at different points in time after graduation. We first trace post-graduation publication activities, where ongoing publication activities, either in academic or non-academic settings, provide evidence that PhD graduates remain active researchers. And then estimate the likelihood of choosing academic and industrial research careers, conditional on publishing. We also explore the mobility patterns of those graduates who remain active in research, across both organizations and countries.

Building a large-scale dataset such a Doc-Track poses substantial conceptual and computational challenges, which we addressed by developing a five-step methodology. First, we cleared and harmonized names and surnames in both national EDT repositories and a widely used bibliometric database, i.e., Elsevier Scopus. Second, for each EDT

repository, we produced all possible combinations of first names, initials, and surnames for each graduate and matched them to all the name variations associated with the Scopus author IDs to create a list of potential PhD-author matches. Third, for each EDT repository, we produced a manually curated dataset of PhD-author true and false matches from which we built training, test, and evaluation sets. Fourth, we applied the Random Forest machine learning algorithm, trained on the training sets, to classify positive and negative matches. The final linked dataset demonstrates high levels of precision and recall rates.

This systematic record linkage procedure is transparent and applicable to various national contexts, and the data generated can be applied to a variety of research questions and international comparative studies. Our study aims to address the gap in the lack of comprehensive studies that cover different national contexts.

We show that the likelihood of having a long-term research career has declined across cohorts and for all countries throughout the last 20 years, net of any cyclical effect due to more R&D funding and other macroeconomic conditions in specific years. Short-term research careers, such as in the years immediately following the graduation, are in decline, too. Moreover, we find that sustained publication engagement is increasingly more likely to be concentrated in selected academic institutions for some disciplines, while the probability of contributing to scientific publishing from corporate settings is increasing but still low.

At the individual level, the two most important predictors for persistency in research are gender and publications during the PhD. We find that, all else equal and in all countries, female graduates are less likely to have a long-term research career and that the gender gap does not close across cohorts. Yet, important cross-country differences exist and persist. We also find that graduates who engaged in publishing early on during their studies are much more likely to keep publishing later on than those who did not, but that also for them the probability to have a long-term research career decreases across cohorts.

Conditional on having such a career, it is increasingly likely that researchers change organization and country to pursue it, with the geographic mobility being most likely explained by increasing competition in the job market and associated internationalization requirements and the increasing share of foreign graduates in all countries, both from the European Union and outside it.

The remainder of the paper is organized as follows. Section 2 describes the various national data sources to retrieve information about PhD recipients. Section 3 outlines the record linkage methodology used to match dissertations with Scopus author profiles. In Section 4 we describe our strategy to tracing doctorate recipients' publication activities during time and between countries. Section 4 reports the main regression results. Section 5 reports the main regression results and Section 6 concludes.

2. Data and methods

2.1 Data sources

We draw on two complementary sources of large-scale administrative and bibliographic data. Concerning the former, we combine information from five national EDT repositories, all of them originating from legal obligations for universities to either deposit their doctoral dissertations at national libraries or to make them otherwise accessible via official initiatives. They are respectively: *theses.fr*, maintained by ABES, the French national bibliographic agency of higher education; the collections and metadata maintained by DNB, the German National Library Germany; TESEO, maintained by the Spanish Ministry of Science, Innovation and Universities; Narcis, a digital platform maintained until recently by the Dutch National Center of Expertise and Repository for Research Data (DANS); and the catalogue maintained by ÖNB, the Austrian National Library.

The French and Spanish repositories are the most stable and complete. They can be regarded as the standard of reference in terms of data quality. Each thesis it records is identified through a unique code and comes with title, language, graduate's name and surname, supervisor and co-supervisors' names and surnames, defense date, discipline, and institution of defense. All other repositories contain similar information, albeit not always as complete and with important cross-country differences. In particular, disciplinary classification is missing for both Austria and the Netherlands, so that we had to infer it from either the dissertations' titles and keywords or the supervisors' publications and their journal classifications. Once solved this problem, we harmonize disciplines across countries by classifying each dissertations into one of five broad categories: i) *Engineering* (comprising General Engineering, Chemical Engineering, and Energy); ii) *Life Science*s (comprising Agricultural and Biological Sciences, Biochemistry, Genetics and Molecular Biology, Immunology and Microbiology, Neuroscience, Pharmacology, Toxicology and Pharmaceutics); iii) *Mathematics & Computer Sciences* (including Mathematics and Computer Science); iv) *Physics* (comprising General Physics and Astronomy, Material Science, Environmental Science, Earth and Planetary Sciences, and also Chemistry as a neighboring discipline); and v) *Medicine* (comprising Medical Science, Nursing, Veterinary, Dentistry, and Health Professions). It is important to stress a peculiarity concerning Medicine in Germany, whose education system equates all medical dissertations produced at the end of single-cycle degrees to doctoral ones, whereas in other countries they are considered as master theses. This makes data for German medical dissertation hardly comparable to those of other countries. Table 1 reports summary information on the consistency of each repository, in total and for the STEMM subset.

Table 1. EDT sources and DOC-TRACK coverage

Country	Sources	Organization	Coverage	Number of theses, of which STEMM
France	*theses.fr*	Agence Bibliographique de l'Enseignement Supérieur (ABES)	All universities, 2000-2020	257,739 theses, of which 166,607 STEMM (65%)
Germany	DNB catalogue; DissOnline	Deutsche Nationalbibliothek (DNB)	All universities, 2000-2020	544,237 theses, of which 420,927 STEMM (77%)
Spain	TESEO	Spanish Ministry of Science, Innovation and Universities	All universities, 2000-2020	204,506 theses, of which 113,772 STEMM (56%)
Netherlands	Narcis	Dutch National Center of Expertise and Repository for Research Data (DANS)	All universities, 2000-2020	81,571 theses, of which 53,925 STEMM (66 %)
Austria	ONB catalogue	Österreichische Nationalbibliothek (ONB)	All universities, 2000-2020	49,808 theses, of which 29,496 STEMM (59%)

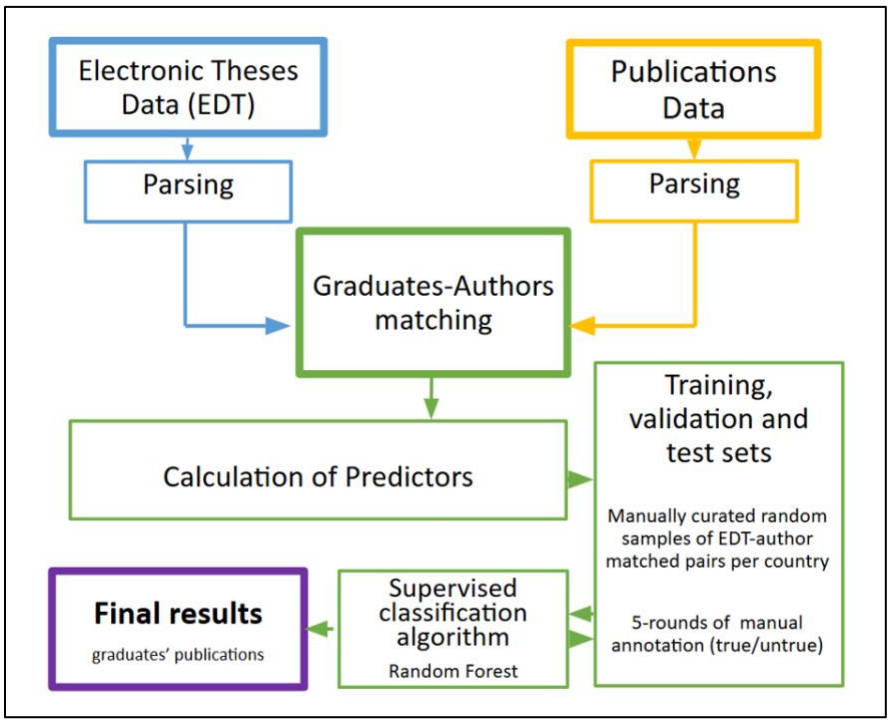
Concerning bibliographic data, our main source of information is Scopus, a very large commercial database maintained by the academic publisher Elsevier. The main reason for choosing this source is the presence and reliability of unique identifiers for authors (Scopus AUID), which provides a highly useful research tool when it comes to find the doctoral graduates' publication, based on name matching. To the extent that the same scientific author (with a corresponding AUID) appears with alternative name representations in different publications, we can assign all of them to the doctoral graduates whose name match just one representation.

Before proceeding to the match, the author data also require substantial parsing. First, we keep all publication types. Second, we exclude publications with authors lacking all information about either names or surnames but keep cases where only the initial of the first name is included together with surnames. Third, we standardize both the graduates' and authors' names to ensure comparability. Last, we generate different name variants for each EDT graduate to account for all potential variations in spelling and structure across publications which may be present in all the name representations associated to each Scopus AUID.

2.2 Linking doctorate recipients to scientific authors

The objective of our linkage approach is first to identify as many potential matches as possible between EDT graduates and publication authors (i.e., maximize recall), and then to minimize the number of incorrect linkages (i.e., improve precision). This problem can be framed as a classification task, which can be addressed using machine-learning methods (see, e.g., Heinisch et al., 2020; Gareth et al., 2013). Various machine learning algorithms are available for classification tasks, including supervised and unsupervised methods (Christen, 2012; Bishop, 2006; Heinisch et al., 2020; Rehs, 2021; Donner, 2022). We opt for a Random Forest supervised classifier and frame our classification process into five key phases: parsing, name matching, creation of training-validation-test sets, training and evaluation of the algorithm, and final classification. They can be summarily described as follows (see Figure 1 for an overview of workflow and Appendix A for full details):

Figure 1: EDT-Scopus record-linkage approach



- Parsing: We first converted the EDT and publications data into a structured format. This included extracting and standardizing relevant information from the EDT repositories and transforming name data into a consistent format across databases for matching.
- Doctoral graduates-authors name matching: Given the computational infeasibility of an exhaustive N-to-M comparison between all the N doctoral graduates in the EDT repositories and all M authors of scientific publications, we applied a pre-selection step based on EDT and publication authors, based on their name similarity (Schnell et al., 2004; Heinisch et al., 2020) and the temporality of the publications with respect to the

defence years. We also excluded outliers (very common names resulting in a disproportionate number of matches) to efficiently reduce the number of comparisons.

- Creation of training, validation, and test datasets: In view of filtering the results of the graduates-authors matching by means of a supervised machine learning method, we constructed a number of manually curated gold standard datasets for training, validation, and testing.
- Training of the classification algorithm: We set a maximum of twelve predictors, per country, as input to the classification algorithms that help predict true positives and true negatives in the original name-based matches. We assign weights to the predictors by means of the Random Forest classification algorithm, making use of the training and validation datasets.
- Final classification and sample construction: We select the best-performing weighing model per country (the one with the highest F1 score) for undertaking the final classification task on the entire set of graduate-author matches.

The resulting matched samples include 248,962 STEMM PhD graduates for Germany, 140,408 for France, 80,982 for Spain, 20,016 for Austria, and 35,418 for the Netherlands. One technical caveat deserves mention: although the record linkage procedure performs well across all countries, small differences in recall of the Random Forest algorithm across countries may affect cross-country comparisons.

2.3 Econometric methodology

We observe the publication activity of doctoral graduates both before and after their graduation and classify each publication as resulting from research undertaken either during the PhD or afterwards. We assume a 4-year duration of doctoral studies and add a year of publication delay (from submission to appearance in a journal or book), irrespective of cohort, country, and discipline. Naming *t* the graduation year, we then classify as produced during the PhD all publications appearing from *t-3* to *t+1*, and all those appearing from *t+2* onward as produced after its completion (see figure 2). We further split the latter into those appearing in the short term, namely from *t+2* to *t+5*, and those appearing in what we define the long term, from *t+6* to *t+9*. Based on the literature, we can safely assume that short-term publications come from some sort of temporary job (a post-doc grant or a fixed-term research assistantship contract), while long-term ones may already come – for a substantial number of graduates – from a more stable academic position, if not tenured at least on tenure-track.

We obtain our final study sample by applying several refinements. First, we remove, for each country, the 5% of graduates who had too many potential Scopus author matches[1], which reduces the sample size from 784,727 to 749,530 observations. Second, we truncate cohorts according to whether our focus is on short-term or long-term publications, respectively at 2017 and 2013, so to preserve the necessary observation margin. Finally, because of

[1] We excluded them for two reasons. First, constructing the Random Forest predictors for classification becomes computationally infeasible because these cases involve thousands of Scopus authors (most of them homonymous false positives) and their publications. Second, the Random Forest classifier would likely erroneously flag multiple Scopus authors as true matches.

missing information on gender, the regressions are estimated on 596,075 graduates for analyses of short-term post-PhD outcomes and on 436,635 graduates for analyses of long-term outcomes.

Building on the resulting dataset, we first examine to what extent the doctoral graduates continue to publish after graduation, first in the short term than in the long one, with the ultimate goal of uncovering common time trends and differences across countries and disciplines. Second, we analyze whether – conditional on publishing in the long term - the doctoral graduates appear to be affiliated with academia or not, and whether and to what extent they change affiliation (leave the academic institution where they graduated) or even country (leave the country where they graduated). We are both interested in purely descriptive statistics (the observed probabilities to publish after graduating and to do so in a specific academic or non-academic setting or country) and in more structural estimates of purely cohort effects, depurated of composition effects (such as the changing mix of disciplines, students' gender, university regulations, such as publication requirements during the doctoral studies) and economic cycle effects (such as the size of the graduation cohort or the macroeconomic conditions at the time of graduation or shortly afterwards).

To do so, we estimate the following linear probability models:

$$Prob(PubShort_{i(cy,co,d)} = 1) = \alpha + \beta X_i + \gamma X_{(cy,co,d)} + \theta X_{i(cy,co,d)} + \varepsilon_i \qquad (1)$$

$$Prob(PubLong_{i(cy,co,d)} = 1) = \alpha + \beta X_i + \gamma X_{(cy,co,d)} + \theta X_{i(cy,co,d)} + \varepsilon_i \qquad (2)$$

$$Prob(AffiliationLong_{i(cy,co,d)} = 1) = \alpha + \beta X_i + \gamma X_{(cy,co,d)} + \theta X_{i(cy,co,d)} + \varepsilon_i \qquad (3)$$

where i is a student graduating in country cy, year co (cohort graduation year) and discipline d ; $PubShort_i$ and $PubLong_i$ are two binary variables taking value one if i publishes after graduation, respectively in the short or long term, and zero otherwise; and $AffiliationLong_i$ stands for a set of different binary variables taking value one if i, conditional on publishing in the long term, does so with at least one specific type of affiliation (non-academic vs academic; different from or identical to her degree-granting institution; or located in a different or the same country of such institution).

The three sets of explanatory variables X include:

X_i: graduate i's gender; a dummy indicating whether i defended the thesis in a university ranked among the top five in its country according to the Leiden research ranking;[2] the size of the i's PhD cohort defined as the number of graduates who defended their thesis in the same graduation year, country, and discipline; the productivity during the PhD (the number of publications; the average number of normalized citations

[2] CWTS Leiden Traditional Ranking 2025 for the years 2006-2009, all sciences, fractional counting, 5 universities per country with highest number of publications in top 1% cited. https://traditional.leidenranking.com/ (October 2025).

received by these publications in the first three years;[3] the number of distinct coauthors); the productivity in the short term (a dummy variable indicating whether *i* did or did not publish in the short term; the number of publications; the average number of normalized citations received by these publications in the first three years; the number of distinct coauthors; only included in equations 2 and 3); a dummy indicating whether *i* had a foreign affiliation during the PhD, as it is the case with joint international programs; a dummy indicating whether *i* had a corporate affiliation during the PhD, as it is the case with PhD programs in partnership with industry; a dummy indicating whether *i* had a foreign affiliation in the short term (only included in equations 2 and 3); and a dummy indicating whether *i* had a corporate affiliation in the short term (only included in equations 2 and 3).

$X_{(cy,co,d)}$: fixed effects for *i*'s country, cohort graduation year, and discipline;[4] plus: a number of macroeconomic variables for the country *cy* in year *co* calculated both during the PhD period and in the short term period (short term period only included in equations 2 and 3). The macroeconomic variables include the deflated GDP per capita, HERD, BERD and GOVERD as percentage of GDP.[5]

$X_{i(cy,co,d)}$: interactions of *i*'s gender, productivity during the PhD, and size of the PhD cohort with the graduation year *co* (added for the analyses showed in Figure 4 of the determinants of long-term publication activity).

[3] The number of citations is normalized by publication year, publication type, and discipline.
[4] We also tested all specifications by including university fixed effects. The results are consistent with those presented throughout the paper.
[5] OECD Main Science and Technology Indicators (MSTI), averages calculated for different periods relative to PhD graduation year (e.g. during the PhD, short term after the PhD): i) GDP per capita (parity purchasing power) adjusted for inflation, in thousand euros (deflated GDP per capita); ii) Higher Education Expenditure on Research and Development, %GDP (HERD); iii) Business Expenditure on Research and Development, %GDP (BERD); iv) Government Expenditure on Research and Development, %GDP (GOVERD). https://stats.oecd.org (July 2025).

3. EDT descriptives

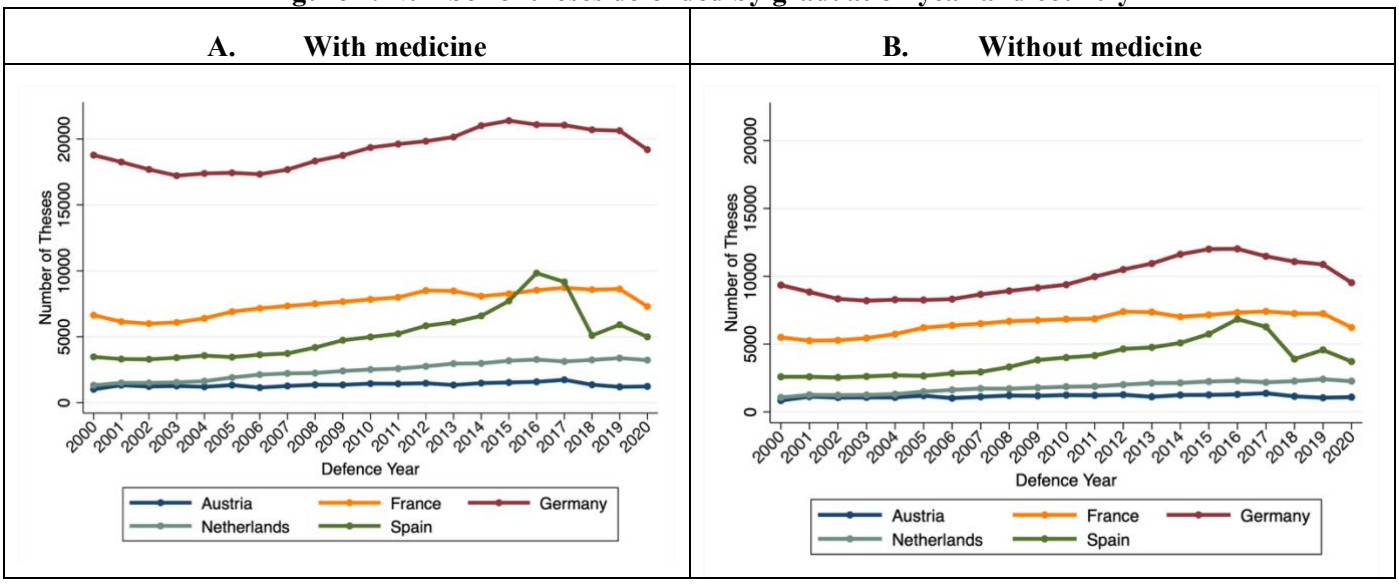
Before moving to the results of our analysis, we provide some detailed description of our EDT data, after treating them as described in the previous section. Concerning time trends, data in table 2 confirm the general increase in the number of doctoral degrees granted each year in all countries, as well as some important cross-country differences, not all of them highlighted by the literature. The table reports the overall number of degrees issued in 2000 and 2020, with and without Medicine (for which Germany, as explained above, does not distinguish between master and doctoral dissertations). In both cases Germany is the only country that exhibits no meaningful increase and stands at the opposite end of the Netherlands, which doubles its numbers. France, Spain and Austria stand in between, with increases ranging from around 10% to more than 40%, regardless of the inclusion of Medicine.

Table 2: Growth in STEMM PhD Graduates by Country (2000–2020)

Cohort	Austria	Germany	Spain	France	Netherlands
Including Medicine					
2000	1,009	18,780	3,472	6,635	1,317
2020	1,229	19,193	4,989	7,294	3,225
% change	21.8%	2.2%	43.7%	9.9%	144.8%
Excluding Medicine					
2000	841	9,348	2,587	5,496	1,065
2020	1,090	9,526	3,714	6,223	2,268
% change	29.6%	1.9%	43.5%	13.2%	113.0%

Figure 2 provides year-per–year information. This reveals that in Spain, the number of dissertations – besides being generally increasing - spiked up dramatically in 2015 and 2016. One explanation for this pattern is the application, in academic year 2014/15, of a reform approved in 2011 (Royal Decree 99/2011) that, among others, limited the duration of doctoral studies, hitherto unregulated, to three years (five for motivated exceptions). This produced a "graduation run" and a rapid exhaustion of the theses backlog (see Corsini et al., 2025, for an overview on the effect of the Royal Decree 99/2011 on Spanish doctoral graduates). A comparison of the two graphs in figure 2 also make clear the extent of Germany's anomaly concerning Medicine, which has to be kept in mind in the rest of the analysis.

Figure 2. Number of theses defended by graduation year and country



The disciplinary makeup of STEM PhDs differs slightly across countries. Table 3 shows the relative shares of Engineering, Life Sciences, Mathematics and Computer Science, Medicine, and Physics among doctoral graduates. France stands out for their emphasis on Physics, with 34% of PhD graduates in this field, and for the importance of theses in Mathematics and Computer sciences relative to other countries (16.6%). Life Sciences account for around one-fourth of all STEM PhDs in Austria, the Netherlands, and Spain, suggesting different research infrastructures and traditions. Austria has also a relative proportion of theses in Engineering, compared to other countries (21.7%). Medicine is overrepresented in Germany, accounting for half of the theses defended. This is due to the institutional organization of Germany, which requires medical doctors to have a PhD degree. These differences are not merely academic: field composition influences publication patterns, labor market trajectories, and international mobility, all career indicators we analyze in later sections, which need to be taken into account when interpreting stay rates in academia.

Table 3: STEMM Field Distribution by Country

Country	Field	Nbr	Share
Austria	Engineering	6,135	21.7%
	Life Sciences	7,641	27.1%
	Mathematics and Computer Science	3,872	13.7%
	Medicine	4,054	14.4%
	Physics	6,524	23.1%
	Total	28,226	100%
Germany	Engineering	60,574	15.0%
	Life Sciences	56,023	13.9%
	Mathematics and Computer Science	25,396	6.3%
	Medicine	197,231	49.0%
	Physics	63,662	15.8%
	Total	402,886	100%
Spain	Engineering	16,491	15.2%
	Life Sciences	25,683	23.7%
	Mathematics and Computer Science	11,515	10.6%
	Medicine	25,909	24.0%
	Physics	28,587	26.4%
	Total	108,185	100%
France	Engineering	26,377	16.6%
	Life Sciences	31,248	19.7%
	Mathematics and Computer Science	26,259	16.6%
	Medicine	20,843	13.1%
	Physics	53,941	34.0%
	Total	158,668	100%
Netherlands	Engineering	7,296	14.1%
	Life Sciences	13,994	27.1%
	Mathematics and Computer Science	5,497	10.7%
	Medicine	13,452	26.1%
	Physics	11,326	22.0%
	Total	51,565	100%

Table 4 shows the gender composition of PhD graduates by country. Spain comes closest to gender parity with a women/men ratio of about 0.94. France and Austria, by contrast, have the lowest ratio, corresponding to 0.62 and 0.63, respectively. Germany and the Netherlands fall somewhere in between. Note that, for the Netherlands, 64.3% of graduates lack information about gender. This is due to the peculiarity of Dutch EDT data, which lack of full graduate name information, making impossible to attribute a gender for most of graduates. These gaps are relevant not only from a gender balance perspective but also because they may shape aggregate productivity and influence retention in academic careers.

Table 4: Gender Composition of STEM PhD Graduates (2000–2020)

Country	Male	Female	Missing info	Ratio F / M
Austria	60.2%	37.8%	2.0%	0.63
Germany	56.0%	42.3%	1.7%	0.75
Spain	51.0%	47.8%	1.2%	0.94
France	60.1%	37.5%	2.4%	0.62
Netherlands	21.1%	14.6%	64.3%	0.69

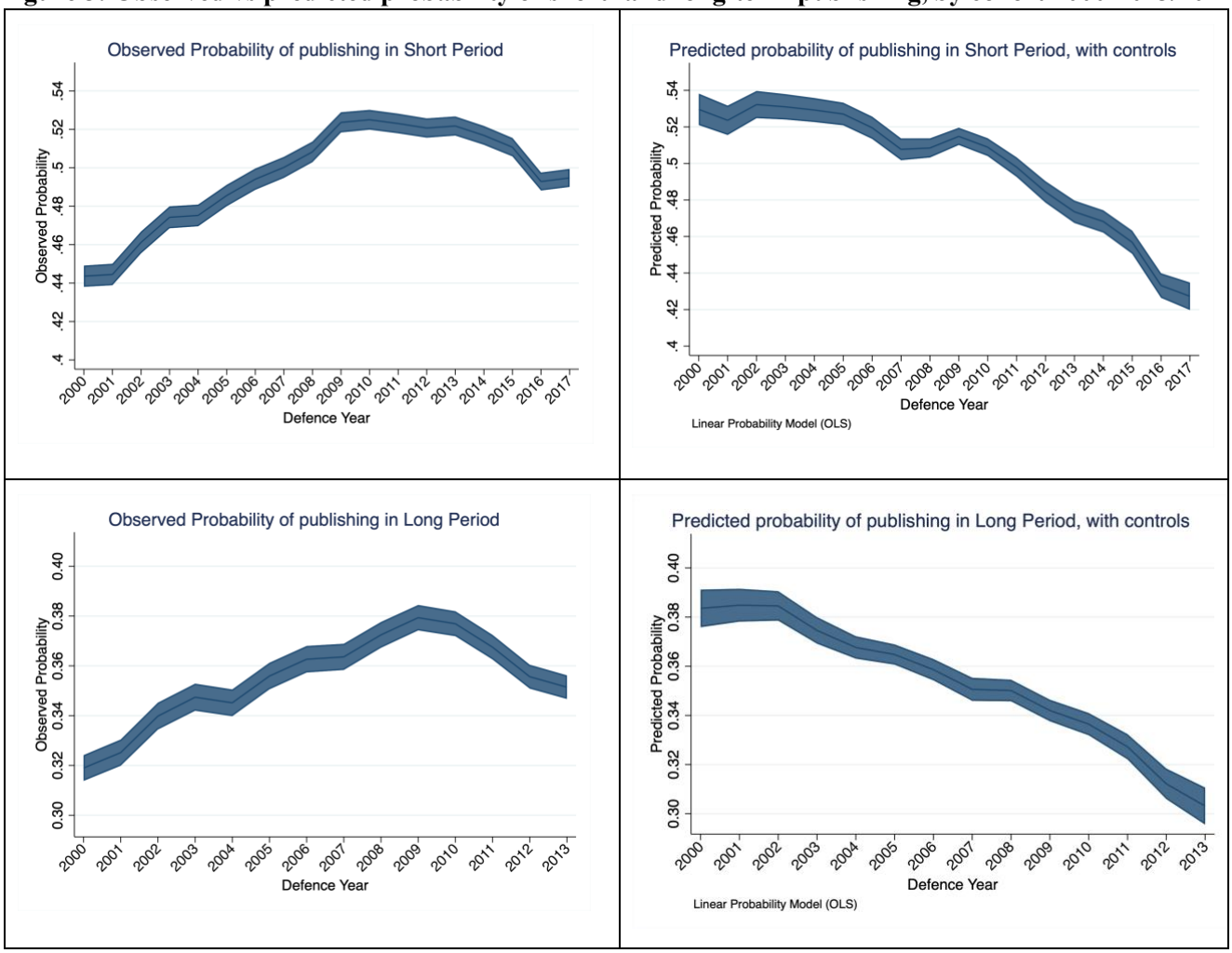
4. Results

Figure 3 plots the observed and predicted probabilities of publishing after graduation in the short and long term (respectively, 2 to 5 and 6 to 9 years after graduation). The predicted probabilities come from the estimation of equations (1) and (2) in section 3 and are obtained by fixing all explanatory variables, but the cohort fixed effects, at their average value. They should be interpreted as baseline estimates of the dependent variable for each cohort, after taking into account composition effects (by country and discipline) as well as the changing conditions of the labour market (size of graduation cohorts and macroeconomic conditions). The full regression tables with the estimated coefficients are available in the Appendix, which also contains additional figures with observed and predicted probabilities by country and field.[6]

We first notice that until around 2010, the observed probability of short-term publishing keeps increasing, just to invert its trend in the following decade. The observed probability of long-term publishing follows a similar pattern, but with the inversion point occurring about two years later. The predicted probability, instead, keeps decreasing across all cohorts, which we interpret as indicative of a structural trend that sees fewer and fewer doctoral graduates engaged in publishing in the long term, after controlling for the economic context at the time of their graduation and soon afterwards.

[6] For the two specifications focusing on PhD productivity, a small number of extreme outliers were removed. These cases correspond to graduates with more than 50 publications during the PhD and represent fewer than 1% of the sample and exert disproportionate influence on the fitted values. In addition, the controls for citations and coauthors accumulated during the PhD were excluded from these models due to their high collinearity with the main explanatory variable.

Figure 3: Observed vs predicted probability of short- and long-term publishing, by cohort 2000-2013/2017



Figures C1 and C2 in the Appendix show that this result holds across countries (with the exception of Germany) and especially disciplines. The same figures in the Appendix also show remarkable differences across countries and disciplines differences exist, not so much with respect to trends, but to levels. Cross-disciplinary differences are intuitively related to the value of a doctoral degree outside the academia, from which most of the graduates' postdoc publications come from (see below). Setting aside Medicine (for the representativeness problems discussed above), it is Engineering graduates who exhibit the lowest estimated probability to publish, whether in the short or long postdoc term, at great distance from the graduates in Mathematics and Computer Science and, further above, those in the Life Sciences and Physics. It is also interesting to notice that the line for Mathematics and Computer Science is especially low, relative to those for Life Sciences and Physics for the more recent cohorts. As for cross-country differences, we know from the literature that Germany stands out for the value attached by industry employers to doctoral training, which explains its line's position at the bottom of the graph; and we presume that something similar may hold, in a more attenuated way, for Austria and the Netherlands. It may also be that our fixed effects for disciplines

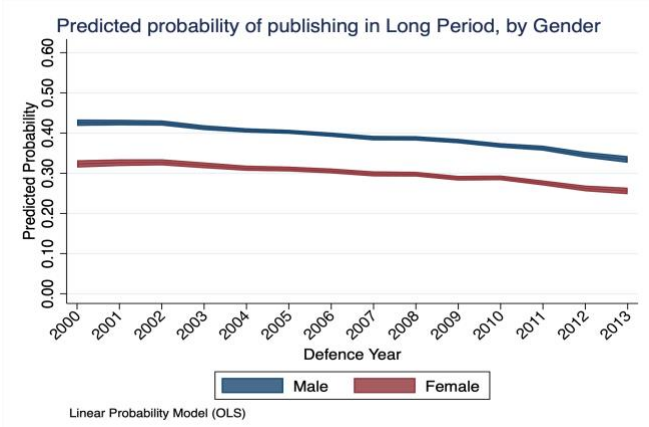
do not capture entirely the composition effects coming from the specific fields of research in different countries, whose exposure to industrial collaboration and research may vary.

Another important observation concerning figure 3 and its analogues in the Appendix relates to the temporal distribution of attrition points, that is of the moments in which the doctoral graduates appear to stop publishing. For the average graduate (see figure 3) the most important attrition point is graduation. Consider, for example, the 2000 cohort: the estimated probability to keep publishing in the short-term it is around 0.54, which implies a 0.46 probability not to start research career; in the long-run, the probability to quit research increases only of 16 percentage points (to around 0.62, that 0.38 probability of publishing). Similarly, for the 2013 cohort, the probability to quit research right after graduation is around 0.52 and 0.70 in the longer term.

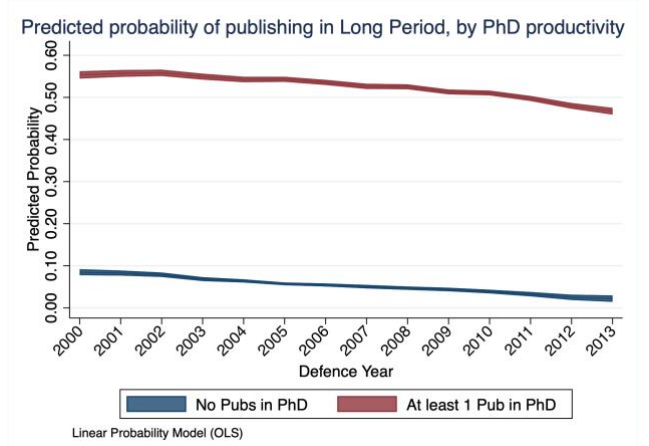
Figure 4 provide details on two determinants of research careers discussed at length in the literature, namely gender and the publishing activity occurring during the doctoral studies, once again based on estimates of equation (2). Concerning gender, ample evidence exists of a gap, by which female graduates exhibit a higher propensity to leave research. Graph A in the figure shows that this is the case also for our sample and that the gap, of around 10 percentage points for the 2000 cohort does not close over time, since the probability of long-term publishing decreases equally for men and women. As for publishing during the PhD, this can be variably interpreted as indicating a strong taste for research on the part of the graduate or of better training (in a more research-oriented university or department, or under the supervision of a more research-oriented mentor) or also of a different orientation and norms of the doctoral programme (towards a career in academic or business R&D). Graph B in the figure shows that – whatever the interpretation – doctoral students with at least a publication during their PhD have a six-time higher probability to keep publishing in the long term, with this difference holding through time. At the same time, though, graph C shows that the marginal effect of any additional publication during the PhD is very small. The graph plots the predicted probabilities of long-term publishing for three productivity categories, namely one publication (approximately the 10th percentile), five publications (between the median and the 75th percentile), and ten publications (around the 90th percentile). The three lines are vertically ordered as expected, with higher PhD productivity associated with higher long-period publication probabilities, but the distance between them is minuscule when compared between publishers and non-publishers. Last, graph D compares predicted probabilities for graduates from small versus large cohorts and somewhat reflects the impact of competition for finding permanent jobs in academia. Belonging to small PhD cohorts (roughly 700 PhD graduates per year, country and discipline) is related to a higher probability of continuing publishing in the long term, than belonging to large cohorts (roughly 9,500 graduates), but the difference is limited and the order reverses in the most recent cohorts.

Figure 4: Determinants of long-term publication activity, by cohort - 2000-2013

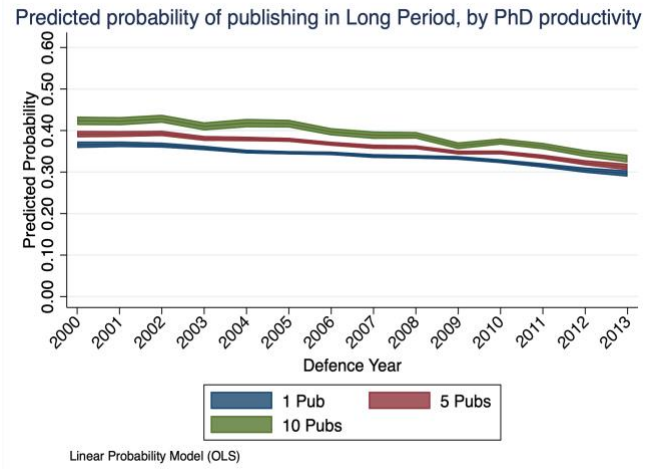
A. Gender



B. PhD productivity - binary



C. PhD productivity – three categories



D. PhD cohort size

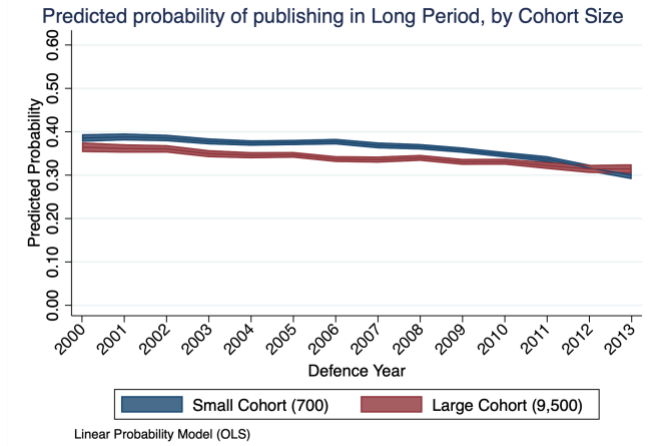
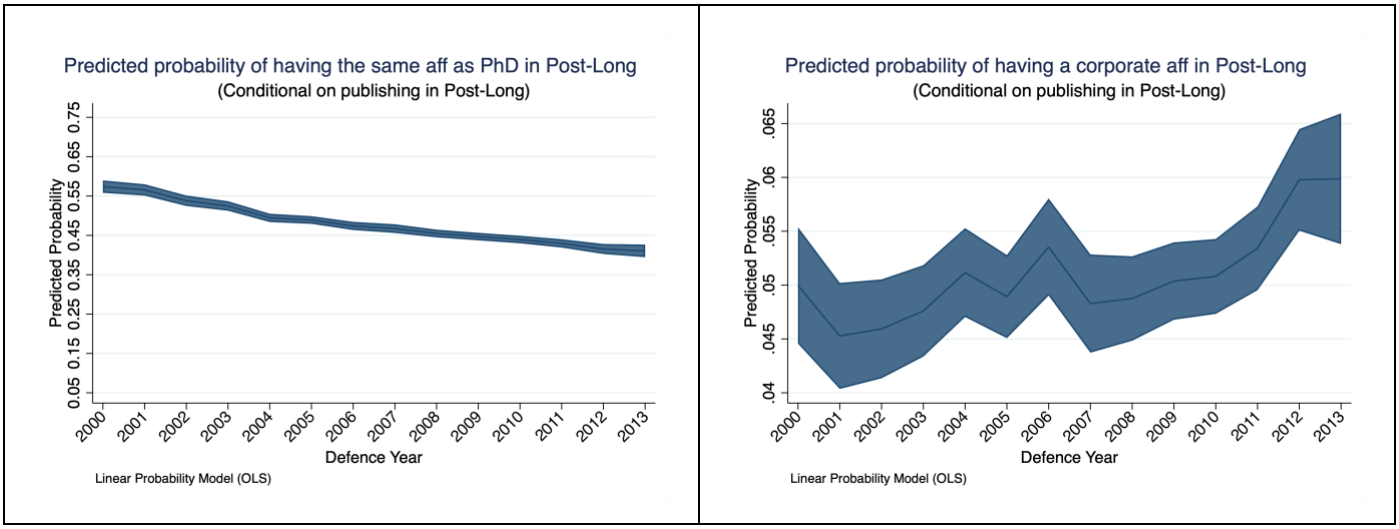


Figure 5 and the following report a set of predicted probabilities for the graduates to publish, over the long-term, with different types of affiliation. All of them are based on estimates of equation (3), with different dependent variables. The full regression tables with the estimated coefficients are available in the Appendix.

Figure 5 illustrate the increasing organizational mobility of the average graduate in our five countries, conditional on publishing in the long term. The left-hand graph shows that the graduates' probability to publish while being affiliated to the same university of graduation declines persistently over time, from around 0.5 for the 2000 cohort to 10 percentage points less for the 2013 one. The overwhelming majority of these affiliations are academic, which indicates that this result is almost exclusively driven by graduates getting jobs in a different university than their *alma mater*. However, the right-hand corner graph shows that the predicted probability to publish with a non-

academic affiliation, albeit always very low, increases over time in an upward trend, which suggests an increasing importance of research-related job placements in the business sector. This is especially noticeable in light of the lower propensity of corporate research to produce scientific publications, relative the academic one.

Figure 5: Predicted probability of long-term publishing with a corporate affiliation, by cohort – 2000-2013



We investigate further this increase in the graduates' mobility by checking whether this goes along with an increase in the institutional stratification, by which most of the graduates who persist in research come from a selected number of top universities and move to less prestigious ones; or whether instead it corresponds to a more circular type of mobility, by which graduates from any university move indifferently to others. To do so we produce some descriptive statistics on the concentration of doctoral graduates by granting institution, at the country level, which we measure with the following Herfindahl–Hirschman Index (HHI):

$$HHI_{cy} = \sum_{u(cy)} share_u^2$$

where $share_u$ is the share of graduates from university u in country cy. We measure concentration in this way for three population of graduates in each country: the entire population of graduates, those who publish in the short term, and those who publish in the long one. We examine separately the cohorts from 2000 to 2009 and those from 2010 to 2020.

We proceed similarly at the disciplinary level, jointly for the five countries. In this case, the concentration index is:

$$HHI_d = \sum_{u(d)} share_u^2$$

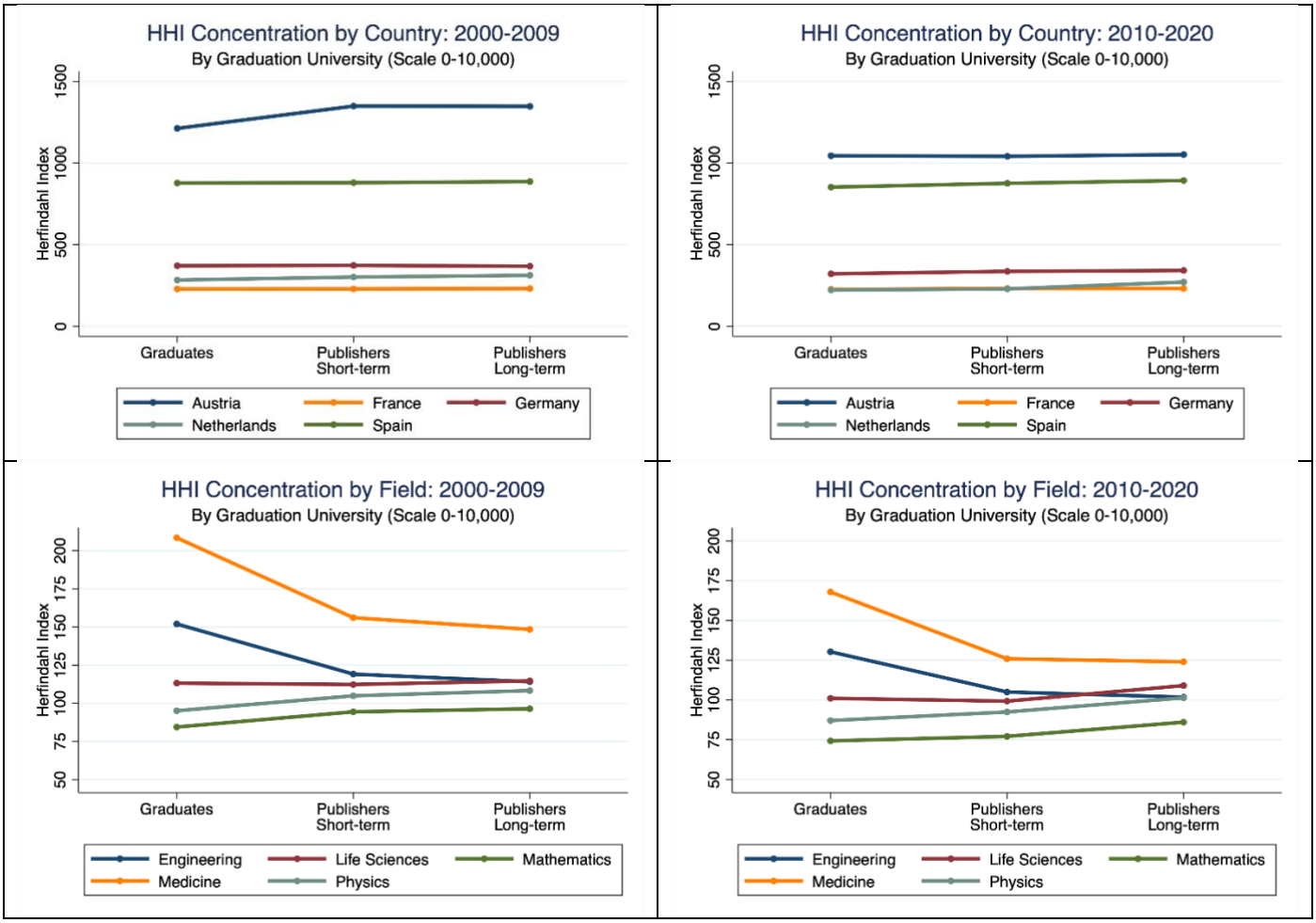
where $share_u$ is the share of graduates from university u with graduates in discipline d.

The top graphs in Figure 6 show our results at the country level. We observe that neither for the less recent cohorts nor

for the more recent ones we observe an increase in concentration when moving from the full population of graduates to of the set of graduates who keep publishing research, either in the short- or the long-term.

The results at the disciplinary level (bottom graphs of Figure 6) tell a slightly different story, with concentration decreasing for both medicine and engineering, especially when moving from the graduates' population to the short-term publishers. These are the disciplines with the lowest stay rate in academia (in the case of Medicine also due to the spurious presence of master students in the data for Germany) and suggests that graduates from the institutions that host the largest number of doctoral students are more likely to quit research, especially academic research, right after graduation, but also in the long term. For the other disciplines, we observe the opposite trend, albeit less marked. In this case, the top institutions (in terms of degrees granted) produce graduates who are more likely to stay in research.

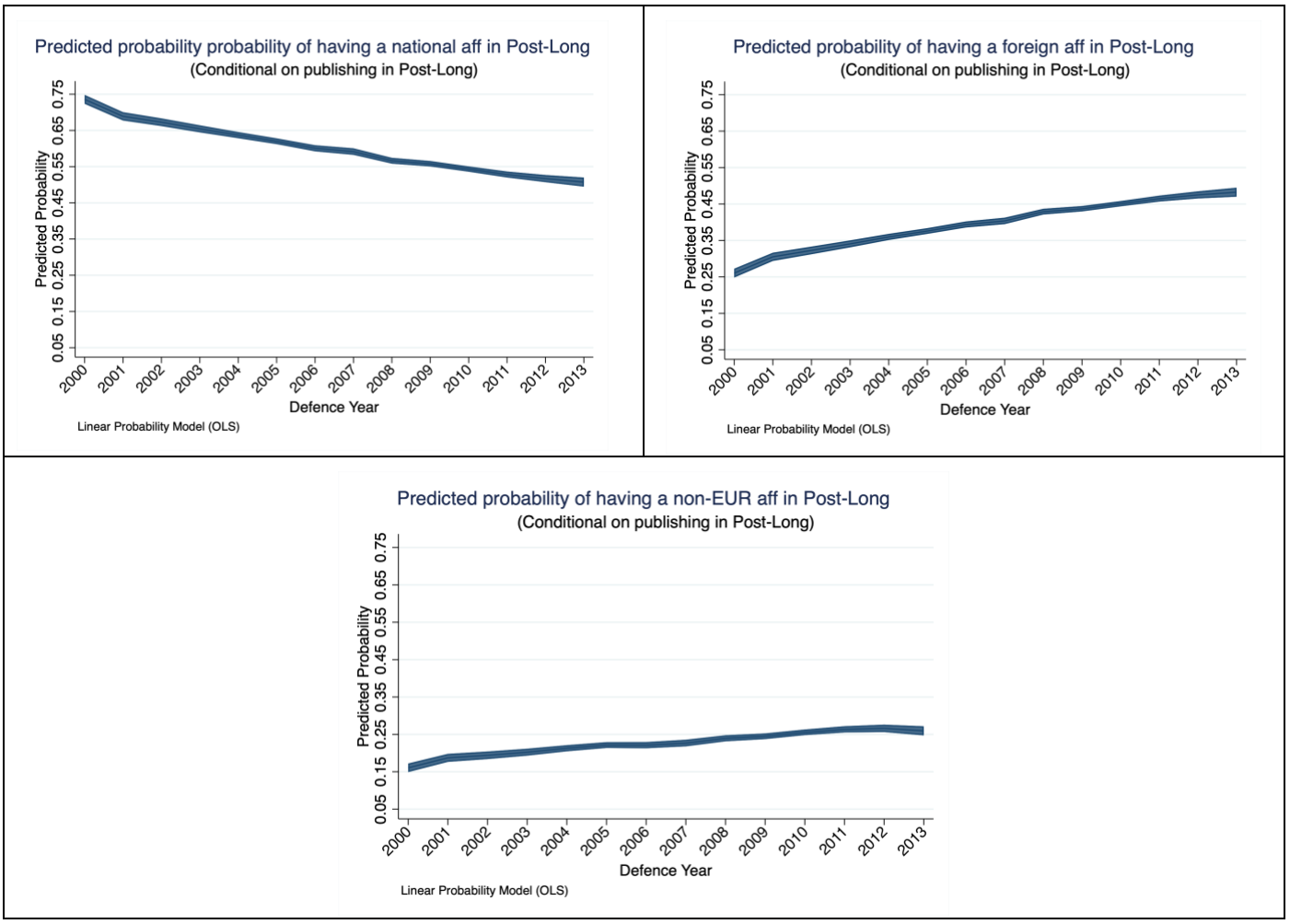
Figure 6. Concentration by degree granting institution by country discipline, 2000-09 and 2010-20 cohorts



Like other countries with a strong university system, the five European countries in our sample have all known a great influx of foreign students, including at the doctoral level. At the same time, they have both introduced a

number of measures – in accordance with the European Union - favoring their academics' mobility across institutions and across countries in the European Research Area.

Figure 7: Predicted probability of affiliation types on long-term publication, by cohort – 2000-2013



The top graphs of Figure 7 show that, conditional on publishing in the long term, the probability to do with a domestic affiliation (namely, an affiliation in the same country of graduation) declines persistently across cohorts, while the opposite holds for the probability to get a foreign affiliation (in a different country than that of graduation). The latter, in particular, moves from around 0.25 for the 2000 cohort to around 0.45 in 2013. At the same time, the bottom graph shows that the probability to get an affiliation outside Europe is also increasing, from 0.15 for the 2000 cohort to 0.25 in 2013, which suggests that only a fraction of international mobility of graduates who persist in their research career descends from an increasing mobility within the European Research Area. This fraction, however, appears to be increasing, as the probability line in the top-right graph is steeper than that in the bottom one. Graphs in figure C3 in the Appendix also show that the predicted probability to publish with a

US affiliation is not increasing: this excludes the existence of a significant brain drain and once again points at the increasing share of foreign graduates and integration of the European Research Area as the main factors behind the increasing international mobility. No differences emerge across countries or disciplines.

5 Conclusions

This study demonstrates the potential of large-scale record linkage for advancing our under-standing of doctoral education and research careers and provides new evidence on research careers in Europe, where there is a notable paucity of international longitudinal data on research careers paths.

By linking national ETD repositories to individual publication records, we constructed the Doc-Track database: a harmonized dataset covering STEMM PhD graduates from five European countries over a 21-year period, which is currently being extended to more countries with the support of the EPO-ARP programme. The linkage approach proved to be transferable across different national contexts and offers several advantages: it provides retrospective, relatively unbiased information on the full population of doctoral graduates; it is not subject to attrition or selective participation typical of survey-based studies; and it allows for consistent cross-national comparisons over time.

Building on Doc-Track, we have explored the likelihood of observing continuous engagement or exit from publication activities by PhD graduates across different countries and over time. Our findings reveal differences over time and across countries and disciplines, but more importantly, we show some common trends controlling for those differences. First, we find that the likelihood of having a long-term research career has declined throughout the last 20 years, net of any cyclical effect due to more R&D funding and other macroeconomic conditions in specific years. Second, sustained publication engagement is increasingly more likely to be concentrated in selected academic institutions for some disciplines, while the probability of contributing to scientific publishing from corporate settings is still modest but growing. Third, it is increasingly likely that European PhD graduates change organization and country to pursue a research career. At the individual level, the two most important predictors for persistency in research are gender (female graduates are more likely to stop publishing) and publications during the PhD.

Taken together, these results underscore both the value of large-scale record linkage for studying research careers and the need for coordinated international efforts to monitor and support the evolving trajectories of doctoral graduates. The Doc-Track data-mining and record-linkage methods are scalable and transferable to additional countries, paving the way for the creation of a permanent observatory of doctoral graduates' careers.

References

Agarwal, R. and A. Ohyama (2013). Industry or academia, basic or applied? career choices and earnings trajectories of scientists. *Management Science 59* (4), 950–970.

Auriol, L., 2010. *Careers of Doctorate Holders: Employment and Mobility Patterns,* OECD Science, Technology and Industry Working Papers No. 2010/4. Organisation for Economic Co-operation and Development: Paris

Auriol, L., Misu, M. and Freeman, R.A., 2013. *Careers of Doctorate Holders: Analysis of Labour Market and Mobility Indicators.* OECD Science, Technology and Industry Working Papers No. 2013/4. Organisation for Economic Co-operation and Development: Paris

Balsmeier B, Pellens M. Who makes, who breaks: Which scientists stay in academe? Economics Letters 2014; 122(2):229–32

Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Information Science and Statis-tics. New York, NY: Springer.

Buechele, S., G. Buenstorf, M. Huegel, J. Koenig, and M. Theissen (2025). Is the dominance of graduates from top-tier universities among tenured faculty driven by prestige or output? evidence from 50 years of university appointments in Germany. Discussion Paper 16-2025, MAGKS Joint Discussion Paper Series in Economics.

Buenstorf, G., J. Koenig, and A. Otto (2023, August). Expansion of doctoral training and doctorate recipients' labour market outcomes: evidence from German register data. *Studies in Higher Education 48* (8), 1216–1242. Publisher: Routledge eprint: https://doi.org/10.1080/03075079.2023.2188397.

Buenstorf, G., J. Koenig, and A. Otto (2024). Keeping up with the max plancks? germany's quest for university excellence and the role of public research institutes in doctoral education. *Scientometrics*, 1–42.

Carriero, R., Coda Zabetta, M., Geuna, A. and Tomatis, F., 2024. Investigating PhDs' early career occupational outcomes in Italy: individual motivations, role of supervisor and gender differences. *Higher Education*, *87*(5), pp.1375-1392.

Christen, P. (2012). *Data Matching: Concepts and Techniques for Record Linkage, Entity Resolution, and Duplicate Detection*. Data-Centric Systems and Applications. Berlin, Heidelberg: Springer.

Corsini, A., M. Pezzoni, and F. Visentin (2022). What makes a productive PhD student? *Research Policy 51* (10), 104561.

Cyranoski, D., N. Gilbert, H. Ledford, A. Nayar, and M. Yahia (2011). Education: the PhD factory.*Nature 472* (7343), 276–279.

Donner, P. (2022). Algorithmic identification of ph. d. thesis-related publications: a proof-of-concept study. *Scientometrics 127* (10), 5863–58

Fan, X., J. Wang, X. Pu, L. Zhou, and B. Lv (2011). On graph-based name disambiguation. *Journal of Data and Information Quality 2* (2), 1–23.

Ganguli, I. and MacGarvie, M. (2025) "International students' migration: policy impacts and implications for innovation." In: LIssoni F. and Morrison A. (eds.) *A Research Agenda for Migration and Innovation*,

pp. 129-150. Edward Elgar Publishing

Gareth, J., D. Witten, T. Hastie, R. Tibshirani, et al. (2013). *An introduction to statistical learning*, Volume 112. Springer.

Geuna, Aldo, and Sotaro Shibayama. "Moving out of academic research: Why do scientists stop doing research?." In Geuna, A. (ed.) *Global mobility of research scientists: The economics of who goes where and why*. Academic Press

Hancock, S., 2023. Knowledge or science-based economy? The employment of UK PhD graduates in research roles beyond academia. *Studies in Higher Education*, *48*(10), pp.1523-1537.

Heinisch, D. P., J. Koenig, and A. Otto (2020). A supervised machine learning approach to trace doctorate recipients' employment trajectories. *Quantitative Science Studies 1* (1), 94–116.

Kahn, S. and MacGarvie, M.J., 2016. How important is US location for research in science?. *Review of Economics and Statistics*, *98*(2), pp.397-414.

Kahn, S. and D. K. Ginther (2017). The impact of postdoctoral training on early careers in biomedicine. *Nature biotechnology 35* (1), 90–94.

Klie, J.-C., R. E. d. Castilho, and I. Gurevych (2024). Analyzing dataset annotation quality management in the wild. *Computational Linguistics 50* (3), 817–866.

Koenig, J. (2022). Postdoctoral employment and future non-academic career prospects. *Plos one 17* (12), e0278091.

Koenig, J. (2024). Costs and benefits of a formal academic qualification beyond the PhD. *Higher Education*, 1–35.

Kwon, D., 2025a. How many PhDs does the world need? Doctoral graduates vastly outnumber jobs in academia. *Nat*ure, 643(8070), pp.16-17.

Larivière, V. (2012). On the shoulders of students? The contribution of PhD students to the advancement of knowledge. Scientometrics 90 (2), 463–481.

Marini, G. and Henseke, G., 2023. Is a PhD worth more than a Master's in the UK labour market? The role of specialisation and managerial position. Studies in Higher Education, 48(10), pp.1538-1550

Martínez, C. and S. Parlane, 2023, Academic scientists in corporate R&D: a theoretical model, Research Policy, 52, 5, 104744

Milojević, S., Radicchi, F. and Walsh, J.P., 2018. Changing demographics of scientific careers: The rise of the temporary workforce. *Proceedings of the National Academy of Sciences*, *115*(50), pp.12616-23

OECD. 2021. Reducing the precarity of academic research careers. OECD Science, Technology and Industry Policy Papers 113. OECD. Paris.

Okrent, A. and Burke, A., 2021. *Where are they now? Most early career US-trained S&E doctorate recipients with temporary visas at graduation stay and work in the United States after graduation*. NSF 21-336. Alexandria, VA: National Science Foundation. Available at https://ncses.nsf.gov/pubs/nsf21336/

Opsomer, J., Chen, A., Chang, W.Y., Foley, D 2021. *US employment higher in the private sector than in the education sector for US-trained doctoral scientists and engineers: Findings from the 2019 survey of doctorate recipients*. NSF 21-319. Alexandria, VA: National Science Foundation. Available at https://ncses.nsf.gov/pubs/nsf21319/

Recotillet, I. (2007). PhD graduates with post-doctoral qualification in the private sector: Does it pay off?

Labour 21 (3), 473–502.

Rehs, A. (2021). A supervised machine learning approach to author disambiguation in the web of science. *Journal of Informetrics 15* (3), 101166

Roach, M. and H. Sauermann (2017). The declining interest in an academic career. *PLOS ONE 12* (9), e0184130. .

Sarrico, C.S., 2022. The expansion of doctoral education and the changing nature and purpose of the doctorate. *Higher Education*, *84*(6), pp.1299-1315.

Sauermann, H. and M. Roach (2012). Science PhD Career Preferences: Levels, Changes, and Advisor Encouragement. *PLOS ONE 7* (5), e36307.

Schillebeeckx, M., B. Maricque, and C. Lewis (2013). The missing piece to changing the university culture. *Nature biotechnology 31* (10), 938–941.

Schneijderberg, C. (2020). Higher education professionals, a growing profession. In *The Interna-tional Encyclopedia of Higher Education Systems and Institutions*, pp. 731–736. Springer.

Schnell, R., T. Bachteler, and S. Bender (2004). A toolbox for record linkage. *Austrian Journal of Statistics 33* (1&2), 125–133.

Shibayama, S. (2022). Development of originality under inbreeding: A case of life science labs in japan. *Higher Education Quarterly 76* (1), 63–75.

Shin, D., T. Kim, J. Choi, and J. Kim (2014). Author name disambiguation using a graph model with node splitting and merging based on bibliographic information. *Scientometrics 100* (1), 15–50

Stephan P (2012) Research efficiency: Perverse incentives. *Nature* 484:29

Stephan, P., 2013. How to exploit postdocs. *BioScience*, *63*(4), pp.245-246.

Stephan, P. and Ma, J., 2005. The increased frequency and duration of the postdoctorate career stage. *American Economic Review*, *95*(2), pp.71-75.

Appendix A Matching EDT repositories to Publication Data

To identify potential matches between doctoral graduates (authors of dissertations) and unique authors in Scopus (authors of publications), we conducted a many-to-many exact match using both the standardized and the name variants. We opted for exact rather than fuzzy string matching due to both the high quality of name metadata in our sources and the computational infeasibility of string-distance calculations at the scale of our operations. This procedure yielded at least one author match for over 95.2% of the doctoral graduates. Match rates vary by country, with Spain achieving nearly full coverage, 99.6%, and Austria the lowest, 93.0% (France: 98.2%; Germany: 93.1%; the Netherlands: 94.6%). While these figures are indicative of a high recall, they also suggest very low precision, which we need to improve both with the application of a few rules and then by means of our machine learning algorithm. Notice that low precision may arise from both 1-to-1 false positives (one graduate matched, wrongly, to one author) and 1-to-M' false positives (one graduate matched to m authors, M'≤M of which are wrong).[7]

We then produced, for each country, a random sample of graduate-author pairs to be used for training, validating, and testing the model. All countries' samples corresponded to around 5000 graduate-authors, more precisely: 4,058 matches for France; 7,159 for Spain; 5,101 for Germany; 5,722 for Austria; and 4,776 for the Netherlands.[8] Independent annotators manually annotated all the sampled matches, based on a three-stage procedure aiming at ensuring consistency and reducing classification errors. The multi-stage annotation process was designed to produce a reliable gold standard dataset for training and testing. The resulting datasets remain unbalanced, with the proportion of negative (0) and positive (1) labels as follows: 61–39% for France, 80–20% for Spain, 77–23% for Germany, 76–24% for Austria, and 78–22% for the Netherlands. Class imbalance of this magnitude is common in binary classification tasks involving real-world data (e.g., He and Garcia, 2009; Fernández et al., 2018). To mitigate imbalance issues, we applied stratified cross-validation to preserve class proportions during training and validation, and used a proper machine learning algorithm, i.e., the

[7] As long as the disambiguation used by Elsevier to produce the Scopus IDs may include some false negatives (the same author receives different Scopus author IDs), it could be the case that the number of mistakes in *1-to-M* matches may be inferior to N-to-1. Absent reliable performance statistics for the Elsevier's disambiguation, we therefore decided not to drop 1-*to*-*N* matches, but to treat them with our machine learning algorithm as separate entities.

[8] The number of graduate-authors is based on a random sample of 1500 doctoral graduates from each country who have at least one matched author.

Random Forest.[9]

We trained a Random Forest classification algorithm with the manually annotated data produced. This specific type of machine learning algorithm has been widely adopted in similar classification contexts (e.g., Fan et al., 2011; Shin et al., 2014) and compares favourably to alternative approaches such as logistic regressions and AdaBoost (cf. Heinisch et al., 2020; Rehs, 2021). In particular, Random Forest algorithms are robust to class imbalances, handle high-dimensional feature spaces well, are less prone to overfitting, and perform efficiently with large datasets. Training a Random Forest algorithm requires, besides the data, the choice of a number of features to which the algorithm assigns weights to maximise its performance, and the choice of one or more performance indicators. Concerning the latter, we opted for using the average F1 score.[10] As for the former, we chose up to 12 features of the doctoral graduate-author matches, grouped into five categories: i) Social proximity (such as the presence, estimated with a low Levenshtein distance between names, of the graduate's supervisor or of a member of the doctoral committee among the co-authors of matched publications); ii) Geographic alignment (such as the presence, among the matched author's affiliations, of the country, city, or of the graduate's institutional alma mater); iii) Topical similarity (such as a significant overlap of the text strings containing the titles of the graduate's dissertation and the author's publication titles, or the overlap between disciplines or keywords); iv) Name similarity (such as a low Levenshtein distance between the text strings containing the standardized name forms of the graduate and the publication author); and v) publication productivity (such as the author being more active in publishing around the period of the graduate's doctoral studies and defence). We trained and tested separately one Random Forest algorithm for each country. In each case, we conducted stratified cross-validation. The algorithm for training and validation was implemented on 90% of the manually annotated dataset of each country, extracted randomly, but with a stratification to preserve the class distribution between true and false matches to deal with the imbalance in the data.[11]

[9] We also experimented with the Synthetic Minority Over-sampling Technique (SMOTE) to increase the representation of the positive class. This approach slightly improved the recall of our models but at the cost of reducing precision. Since our primary concern is maintaining high precision, we chose not to implement SMOTE in the final models.

[10] The F1 score is the harmonic mean of precision and recall, balancing the trade-off between false positives and false negatives.

[11] Specifically, we conducted a stratified 5-fold cross-validation procedure combined with an exhaustive grid search to tune two hyperparameters: the number of trees (*ntree*) and the number of variables considered at each split (*mtry*). The number of trees was varied from 500 to 2,000 in increments of 50, while *mtry* was tested across the values 1, 2, 3, 4, and the maximum value of features used for a given country. The data were divided into five equally sized subsets, which were

The results of the trained country-specific Random Forest models were tested against the 10% records from the manually annotated datasets that were not used for training. In terms of precision and recall, all models perform rather strongly, as follows:

- Germany: 93.5% precision, 87.8% recall
- France: 96.1% precision, 94.2% recall
- Spain: 96.2% precision, 89.5% recall
- Austria: 95.2% precision, 88.2% recall
- Netherlands: 99.0% precision, 95.3% recall[12]

extracted randomly and stratified. There were five iterations, in each of which we used four out of five subsets for model training and held the fifth one out for validation. The validation subset was rotated in each iteration.

[12] The 99% precision observed for the Netherlands is partly due to the additional geographical filter applied in step 2, aimed at reducing false positives. By restricting the sample in this way, the Random Forest is applied to a sample where true positives are more prevalent, leading to higher measured precision and recall. However, this filter also excludes some graduate-author pairs that could include true positives. In this case, 2,570 graduates were removed, representing 4.8% of the total Dutch graduates.

Appendix B Regression results

Table B1. Determinants of publication activity, short and long after the PhD. OLS estimates.

	(1)	(2)
	Publishing Short Period (+2,+5)	Publishing Long Period (+6,+9)
2001	-0.0060*	0.0013
	(0.0035)	(0.0027)
2002	0.0026	0.0010
	(0.0036)	(0.0033)
2003	0.0014	-0.0089**
	(0.0037)	(0.0038)
2004	-0.0004	-0.0159***
	(0.0038)	(0.0038)
2005	-0.0025	-0.0187***
	(0.0039)	(0.0038)
2006	-0.0101**	-0.0249***
	(0.0042)	(0.0041)
2007	-0.0219***	-0.0329***
	(0.0045)	(0.0043)
2008	-0.0211***	-0.0334***
	(0.0047)	(0.0047)
2009	-0.0148***	-0.0415***
	(0.0050)	(0.0051)
2010	-0.0207***	-0.0471***
	(0.0054)	(0.0054)
2011	-0.0316***	-0.0563***
	(0.0058)	(0.0059)
2012	-0.0452***	-0.0713***
	(0.0062)	(0.0065)
2013	-0.0561***	-0.0804***
	(0.0065)	(0.0072)
2014	-0.0614***	
	(0.0066)	
2015	-0.0727***	
	(0.0068)	
2016	-0.0964***	
	(0.0071)	
2017	-0.1023***	
	(0.0075)	
Germany	-0.0100	-0.0439***
	(0.0141)	(0.0142)
Spain	0.2716***	0.1777***
	(0.0160)	(0.0158)
France	0.2467***	0.0724***
	(0.0129)	(0.0124)
Netherlands	-0.0071	0.0562***
	(0.0094)	(0.0108)
Life Sciences	0.1398***	0.0448***
	(0.0022)	(0.0019)
Mathematics	0.0378***	0.0159***
	(0.0024)	(0.0022)

Medicine	0.0873***	0.0414***
	(0.0026)	(0.0025)
Physics	0.1123***	-0.0077***
	(0.0022)	(0.0019)
Female	-0.0328***	-0.0367***
	(0.0012)	(0.0011)
TopUni (d)	-0.0007	-0.0014
	(0.0014)	(0.0012)
SizeField (d)	-0.0000***	-0.0000***
	(0.0000)	(0.0000)
PubsDuringPhD (n)	0.0150***	0.0028***
	(0.0003)	(0.0002)
AvgCitDuringPhD (n)	0.0321***	0.0056***
	(0.0018)	(0.0004)
CoauthDuringPhD (n)	-0.0006***	-0.0003***
	(0.0000)	(0.0000)
ForeignDuringPhD (d)	0.2177***	0.0289***
	(0.0030)	(0.0023)
CompanyDuringPhD (d)	0.0368***	0.0136**
	(0.0057)	(0.0061)
GDPDuringPhD	0.0060***	
	(0.0004)	
HERDDuringPhD	-0.0845	
	(0.0623)	
BERDDuringPhD	0.0787***	
	(0.0125)	
GOVERDDuringPhD	0.0169	
	(0.0226)	
PubsShort (d)		0.4435***
		(0.0023)
PubsShort (n)		0.0097***
		(0.0002)
AvgCitsShort (n)		0.0043***
		(0.0005)
CoauthShort (n)		-0.0002***
		(0.0000)
AcademicShort (n)		0.1991***
		(0.0021)
CompanyShort (n)		0.0047
		(0.0052)
GDPshort		0.0024***
		(0.0006)
HERDshort		0.0155
		(0.0605)
BERDShort		0.0447***
		(0.0132)
GOVERDShort		0.1870***
		(0.0264)
Constant	-0.0359	-0.1834***
	(0.0270)	(0.0256)
Adjusted R_sq	0.242	0.508
Observations	596,075	436,635

Table B2. Determinants of different types of affiliations in publications long after the PhD. OLS estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Corporate affiliation	National affiliation	Same affiliation as PhD	Foreign affiliation	German affiliation	Non-EUR affiliation	USA affiliation
2001	-0.0047	-0.0469***	-0.0083	0.0448***	0.0051	0.0266***	0.0094**
	(0.0030)	(0.0058)	(0.0070)	(0.0057)	(0.0036)	(0.0053)	(0.0044)
2002	-0.0040	-0.0631***	-0.0359***	0.0624***	-0.0007	0.0335***	0.0140***
	(0.0030)	(0.0062)	(0.0076)	(0.0061)	(0.0049)	(0.0058)	(0.0047)
2003	-0.0024	-0.0814***	-0.0492***	0.0804***	0.0070	0.0418***	0.0075
	(0.0031)	(0.0066)	(0.0082)	(0.0066)	(0.0066)	(0.0062)	(0.0050)
2004	0.0012	-0.0988***	-0.0794***	0.0994***	0.0017	0.0523***	0.0080
	(0.0032)	(0.0066)	(0.0082)	(0.0065)	(0.0075)	(0.0062)	(0.0050)
2005	-0.0010	-0.1157***	-0.0849***	0.1157***	0.0104	0.0609***	0.0108**
	(0.0032)	(0.0066)	(0.0083)	(0.0066)	(0.0078)	(0.0063)	(0.0051)
2006	0.0036	-0.1351***	-0.0998***	0.1337***	0.0038	0.0605***	0.0049
	(0.0034)	(0.0070)	(0.0089)	(0.0069)	(0.0081)	(0.0067)	(0.0054)
2007	-0.0017	-0.1442***	-0.1067***	0.1434***	0.0095	0.0662***	-0.0005
	(0.0035)	(0.0074)	(0.0093)	(0.0073)	(0.0081)	(0.0071)	(0.0056)
2008	-0.0012	-0.1695***	-0.1191***	0.1688***	0.0112	0.0789***	0.0036
	(0.0034)	(0.0077)	(0.0097)	(0.0076)	(0.0083)	(0.0073)	(0.0058)
2009	0.0004	-0.1777***	-0.1270***	0.1769***	0.0171*	0.0844***	0.0138**
	(0.0034)	(0.0080)	(0.0103)	(0.0079)	(0.0092)	(0.0077)	(0.0061)
2010	0.0008	-0.1925***	-0.1344***	0.1907***	0.0148	0.0949***	0.0109*
	(0.0035)	(0.0083)	(0.0107)	(0.0082)	(0.0102)	(0.0079)	(0.0063)
2011	0.0035	-0.2075***	-0.1442***	0.2047***	0.0154	0.1029***	0.0100
	(0.0039)	(0.0091)	(0.0116)	(0.0089)	(0.0123)	(0.0087)	(0.0069)
2012	0.0098**	-0.2187***	-0.1585***	0.2149***	0.0100	0.1055***	0.0112
	(0.0043)	(0.0100)	(0.0129)	(0.0099)	(0.0148)	(0.0096)	(0.0076)
2013	0.0099**	-0.2284***	-0.1633***	0.2222***	0.0085	0.0989***	0.0081
	(0.0049)	(0.0113)	(0.0144)	(0.0111)	(0.0175)	(0.0107)	(0.0085)
Germany	0.0100	0.0123	-0.0409	-0.0088		0.1853***	0.0922***
	(0.0112)	(0.0230)	(0.0284)	(0.0227)		(0.0229)	(0.0177)
Spain	-0.0551***	0.3019***	0.4845***	-0.2908***	-0.1244***	0.0172	0.0136
	(0.0116)	(0.0254)	(0.0323)	(0.0251)	(0.0233)	(0.0244)	(0.0191)
France	-0.0273***	0.1554***	-0.0131	-0.1456***	-0.1080***	0.1287***	0.0300**
	(0.0083)	(0.0190)	(0.0239)	(0.0187)	(0.0133)	(0.0186)	(0.0143)
Netherlands	-0.0148	0.0125	0.1897***	-0.0148	-0.0896***	0.0427**	0.0281*
	(0.0105)	(0.0196)	(0.0246)	(0.0193)	(0.0191)	(0.0195)	(0.0154)
Life Sciences	-0.0217***	-0.0516***	0.0155***	0.0522***	0.0034	0.0242***	0.0645***
	(0.0020)	(0.0033)	(0.0043)	(0.0033)	(0.0024)	(0.0033)	(0.0024)
Mathematics	-0.0200***	-0.0160***	-0.0417***	0.0149***	-0.0013	0.0029	0.0103***
	(0.0023)	(0.0039)	(0.0048)	(0.0039)	(0.0023)	(0.0039)	(0.0026)
Medicine	-0.0249***	-0.0135***	0.0729***	0.0092**	-0.0074***	0.0119***	0.0635***
	(0.0021)	(0.0041)	(0.0051)	(0.0040)	(0.0021)	(0.0040)	(0.0030)
Physics	-0.0097***	-0.0085***	-0.0103**	0.0083***	0.0267***	-0.0263***	0.0168***
	(0.0021)	(0.0032)	(0.0041)	(0.0032)	(0.0037)	(0.0032)	(0.0022)
Female	-0.0106***	0.0149***	-0.0139***	-0.0161***	-0.0040***	-0.0289***	-0.0085***
	(0.0010)	(0.0021)	(0.0026)	(0.0021)	(0.0014)	(0.0021)	(0.0016)
TopUni(d)	0.0025**	-0.0125***	-0.0273***	0.0132***	0.0045***	0.0037	0.0248***
	(0.0011)	(0.0023)	(0.0028)	(0.0023)	(0.0015)	(0.0023)	(0.0018)

FieldSize (d)	-0.0000***	0.0000***	-0.0000**	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PubsDuringPhD (n)	0.0003***	0.0015***	0.0065***	-0.0015***	0.0000	-0.0013***	0.0003**
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AvgCitsDuringPhD(n)	0.0009***	0.0005**	0.0057***	-0.0005*	0.0012***	-0.0018***	0.0018***
	(0.0002)	(0.0003)	(0.0006)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
CoauthDuringPhD(n)	0.0000	0.0000	-0.0002***	-0.0000	-0.0000***	-0.0000	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ForeignDuringPhD(d)	-0.0052***	-0.0946***	0.1780***	0.0951***	0.0104***	0.0782***	0.0008
	(0.0013)	(0.0028)	(0.0033)	(0.0028)	(0.0021)	(0.0031)	(0.0024)
CompanyDuringPhD (d)	0.1321***	0.0208***	0.1379***	-0.0221***	0.0013	-0.0213***	0.0136**
	(0.0094)	(0.0078)	(0.0105)	(0.0077)	(0.0063)	(0.0073)	(0.0063)
PubsShort(d)	-0.0409***	0.1251***	0.0830***	-0.1136***	-0.0133***	-0.0837***	-0.0316***
	(0.0028)	(0.0047)	(0.0055)	(0.0046)	(0.0023)	(0.0039)	(0.0027)
PubsShort(n)	-0.0004***	-0.0003***	0.0054***	0.0005***	0.0005***	0.0004***	0.0011***
	(0.0000)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AvgCitsShort(n)	0.0007***	-0.0018***	0.0015***	0.0018***	0.0008***	0.0002	0.0048***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0006)
CoauthShort(n)	-0.0000	-0.0000***	-0.0001***	0.0000***	0.0000***	0.0000***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
AcademicShort(d)	-0.0045***	-0.5999***	-0.1610***	0.6027***	0.0605***	0.3484***	0.1770***
	(0.0011)	(0.0024)	(0.0027)	(0.0024)	(0.0016)	(0.0025)	(0.0020)
CompanyShort(d)	0.5384***	-0.0317***	-0.1434***	0.0303***	0.0191***	-0.0045	0.0435***
	(0.0070)	(0.0058)	(0.0067)	(0.0058)	(0.0052)	(0.0053)	(0.0047)
GDPShort	-0.0016***	0.0122***	0.0062***	-0.0119***	0.0006	-0.0060***	-0.0039***
	(0.0005)	(0.0011)	(0.0014)	(0.0011)	(0.0022)	(0.0010)	(0.0008)
HERDShort	0.0858	0.0197	0.1971	0.0141	0.0049	0.3409***	0.2052**
	(0.0542)	(0.1064)	(0.1336)	(0.1048)	(0.0781)	(0.1074)	(0.0843)
BERDShort	-0.0161	0.0570**	0.2177***	-0.0615***	-0.0328*	-0.0438*	-0.0089
	(0.0132)	(0.0239)	(0.0297)	(0.0236)	(0.0190)	(0.0241)	(0.0190)
GOVERDShort	0.0047	0.2208***	0.3795***	-0.2153***	0.0371	-0.3892***	-0.0885***
	(0.0181)	(0.0398)	(0.0480)	(0.0395)	(0.0579)	(0.0389)	(0.0298)
Constant	0.1591***	0.0874**	-0.4395***	0.8644***	0.1168	0.2737***	0.0581*
	(0.0186)	(0.0416)	(0.0537)	(0.0410)	(0.0879)	(0.0400)	(0.0316)
Adjusted R_sq	0.251	0.412	0.131	0.421	0.053	0.204	0.105
Observations	153,162	153,162	153,162	153,162	92,326	153,162	153,162

Table B3. Temporal Evolution of Structural Determinants. OLS estimates.

	(1)	(2)	(3)	(4)
	Publishing Long Period	Publishing Long Period	Publishing Long Period	Publishing Long Period
2001	0.0003	-0.0020	0.0014	0.0029
	(0.0034)	(0.0022)	(0.0029)	(0.0043)
2002	-0.0007	-0.0060**	-0.0015	0.0005
	(0.0039)	(0.0030)	(0.0035)	(0.0047)
2003	-0.0124***	-0.0164***	-0.0072*	-0.0071
	(0.0043)	(0.0035)	(0.0040)	(0.0050)
2004	-0.0192***	-0.0207***	-0.0177***	-0.0110**
	(0.0043)	(0.0036)	(0.0040)	(0.0050)
2005	-0.0226***	-0.0277***	-0.0206***	-0.0097*
	(0.0043)	(0.0036)	(0.0040)	(0.0051)
2006	-0.0299***	-0.0303***	-0.0201***	-0.0068
	(0.0046)	(0.0039)	(0.0043)	(0.0054)
2007	-0.0384***	-0.0343***	-0.0263***	-0.0160***
	(0.0048)	(0.0041)	(0.0046)	(0.0056)
2008	-0.0390***	-0.0379***	-0.0283***	-0.0198***
	(0.0052)	(0.0046)	(0.0051)	(0.0058)
2009	-0.0458***	-0.0411***	-0.0286***	-0.0274***
	(0.0056)	(0.0051)	(0.0056)	(0.0060)
2010	-0.0566***	-0.0459***	-0.0385***	-0.0389***
	(0.0058)	(0.0053)	(0.0057)	(0.0062)
2011	-0.0633***	-0.0522***	-0.0484***	-0.0489***
	(0.0063)	(0.0059)	(0.0062)	(0.0066)
2012	-0.0799***	-0.0597***	-0.0592***	-0.0708***
	(0.0069)	(0.0065)	(0.0069)	(0.0073)
2013	-0.0915***	-0.0628***	-0.0668***	-0.0881***
	(0.0076)	(0.0072)	(0.0076)	(0.0081)
Female	-0.0491***	-0.0334***	-0.0322***	-0.0368***
	(0.0038)	(0.0011)	(0.0011)	(0.0011)
2001 # Female	0.0028			
	(0.0054)			
2002 # Female	0.0047			
	(0.0054)			
2003 # Female	0.0088			
	(0.0055)			
2004 # Female	0.0085			
	(0.0054)			
2005 # Female	0.0099*			
	(0.0054)			
2006 # Female	0.0124**			
	(0.0054)			
2007 # Female	0.0136**			
	(0.0054)			
2008 # Female	0.0135**			
	(0.0054)			
2009 # Female	0.0102*			
	(0.0054)			
2010 # Female	0.0219***			
	(0.0054)			
2011 # Female	0.0159***			

	(0.0053)			
2012 # Female	0.0190***			
	(0.0053)			
2013 # Female	0.0242***			
	(0.0053)			
Germany	-0.0426***	-0.0479***	-0.0419***	-0.0774***
	(0.0142)	(0.0141)	(0.0142)	(0.0151)
Spain	0.1806***	0.1472***	0.1593***	0.1381***
	(0.0158)	(0.0155)	(0.0158)	(0.0166)
France	0.0747***	0.0520***	0.0728***	0.0424***
	(0.0124)	(0.0122)	(0.0124)	(0.0130)
Netherlands	0.0567***	0.0479***	0.0476***	0.0575***
	(0.0108)	(0.0107)	(0.0108)	(0.0113)
Life Sciences	0.0447***	0.0458***	0.0493***	0.0446***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Mathematics	0.0160***	0.0165***	0.0161***	0.0161***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Medicine	0.0412***	0.0411***	0.0342***	0.0412***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Physics	-0.0079***	-0.0142***	-0.0112***	-0.0079***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
TopUni (d)	-0.0014	-0.0026**	-0.0018	-0.0013
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
FieldSize (d)	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PubsDuringPhD (n)	0.0028***		0.0064***	0.0028***
	(0.0002)		(0.0005)	(0.0002)
AvgCitsDuringPhD (n)	0.0056***			0.0056***
	(0.0004)			(0.0004)
CoauthDuringPhD (n)	-0.0003***			-0.0003***
	(0.0000)			(0.0000)
ForeignDuringPhD (d)	0.0289***	0.0108***	0.0158***	0.0289***
	(0.0023)	(0.0022)	(0.0022)	(0.0023)
CompanyDuringPhD (d)	0.0137**	-0.0036	0.0117*	0.0139**
	(0.0061)	(0.0060)	(0.0061)	(0.0061)
PubsShort (d)	0.4435***	0.3783***	0.4247***	0.4434***
	(0.0023)	(0.0024)	(0.0022)	(0.0023)
PubsShort (n)	0.0097***	0.0142***	0.0131***	0.0097***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
AvgCitsShort (n)	0.0043***	0.0040***	0.0040***	0.0043***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
CoauthShort (n)	-0.0002***	-0.0003***	-0.0003***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
AcademicForeignShort (d)	0.1992***	0.1912***	0.1906***	0.1991***
	(0.0021)	(0.0022)	(0.0022)	(0.0021)
CompanyShort (d)	0.0048	0.0113**	0.0055	0.0048
	(0.0052)	(0.0052)	(0.0052)	(0.0052)

GDPShort	0.0025***	0.0025***	0.0023***	0.0028***
	(0.0006)	(0.0006)	(0.0006)	(0.0008)
HERDShort	0.0157	-0.0136	-0.0030	-0.1873***
	(0.0605)	(0.0601)	(0.0608)	(0.0672)
BERDShort	0.0456***	0.0278**	0.0377***	0.0596***
	(0.0132)	(0.0130)	(0.0131)	(0.0135)
GOVERDShort	0.1819***	0.1339***	0.1500***	0.1624***
	(0.0264)	(0.0264)	(0.0263)	(0.0273)
PubsDuringPhD(d)		0.1233***		
		(0.0035)		
2001 # PubsDuringPhD(d)		0.0054		
		(0.0047)		
2002 # PubsDuringPhD(d)		0.0109**		
		(0.0048)		
2003 # PubsDuringPhD(d)		0.0123**		
		(0.0048)		
2004 # PubsDuringPhD(d)		0.0098**		
		(0.0048)		
2005 # PubsDuringPhD(d)		0.0172***		
		(0.0047)		
2006 # PubsDuringPhD(d)		0.0125***		
		(0.0047)		
2007 # PubsDuringPhD(d)		0.0071		
		(0.0047)		
2008 # PubsDuringPhD(d)		0.0097**		
		(0.0047)		
2009 # PubsDuringPhD(d)		0.0007		
		(0.0047)		
2010 # PubsDuringPhD(d)		0.0030		
		(0.0046)		
2011 # PubsDuringPhD(d)		-0.0038		
		(0.0046)		

2012 # PubsDuringPhD(d)		-0.0138***		
		(0.0046)		
2013 # PubsDuringPhD(d)		-0.0235***		
		(0.0045)		
2001 # PubsDuringPhD(n)			-0.0002	
			(0.0006)	
2002 # PubsDuringPhD(n)			0.0006	
			(0.0006)	
2003 # PubsDuringPhD(n)			-0.0006	
			(0.0007)	
2004 # PubsDuringPhD(n)			0.0012*	
			(0.0007)	
2005 # PubsDuringPhD(n)			0.0014**	
			(0.0007)	
2006 # PubsDuringPhD(n)			-0.0006	
			(0.0006)	
2007 # PubsDuringPhD(n)			-0.0008	
			(0.0007)	
2008 # PubsDuringPhD(n)			-0.0007	
			(0.0006)	
2009 # PubsDuringPhD(n)			-0.0032***	
			(0.0007)	
2010 # PubsDuringPhD(n)			-0.0012*	
			(0.0006)	
2011 # PubsDuringPhD(n)			-0.0012**	
			(0.0006)	
2012 # PubsDuringPhD(n)			-0.0020***	
			(0.0006)	
2013 # PubsDuringPhD(n)			-0.0024***	
			(0.0006)	
2001 # FieldSize (d)				-0.0000
				(0.0000)
2002 # FieldSize (d)				-0.0000

				(0.0000)
2003 # FieldSize (d)				-0.0000
				(0.0000)
2004 # FieldSize (d)				-0.0000
				(0.0000)
2005 # FieldSize (d)				-0.0000
				(0.0000)
2006 # FieldSize (d)				-0.0000***
				(0.0000)
2007 # FieldSize (d)				-0.0000*
				(0.0000)
2008 # FieldSize (d)				-0.0000
				(0.0000)
2009 # FieldSize (d)				-0.0000
				(0.0000)
2010 # FieldSize (d)				0.0000
				(0.0000)
2011 # FieldSize (d)				0.0000
				(0.0000)
2012 # FieldSize (d)				0.0000***
				(0.0000)
2013 # FieldSize (d)				0.0000***
				(0.0000)
Constant	-0.1836***	-0.1629***	-0.1537***	-0.0968***
	(0.0256)	(0.0251)	(0.0257)	(0.0292)
Adjusted R_sq	0.508	0.524	0.516	0.508
Observations	436,635	435,481	435,481	436,635

Appendix C Additional Figures

Figure C1: Observed vs predicted probability of publishing shortly and long after the PhD

By graduation year & field

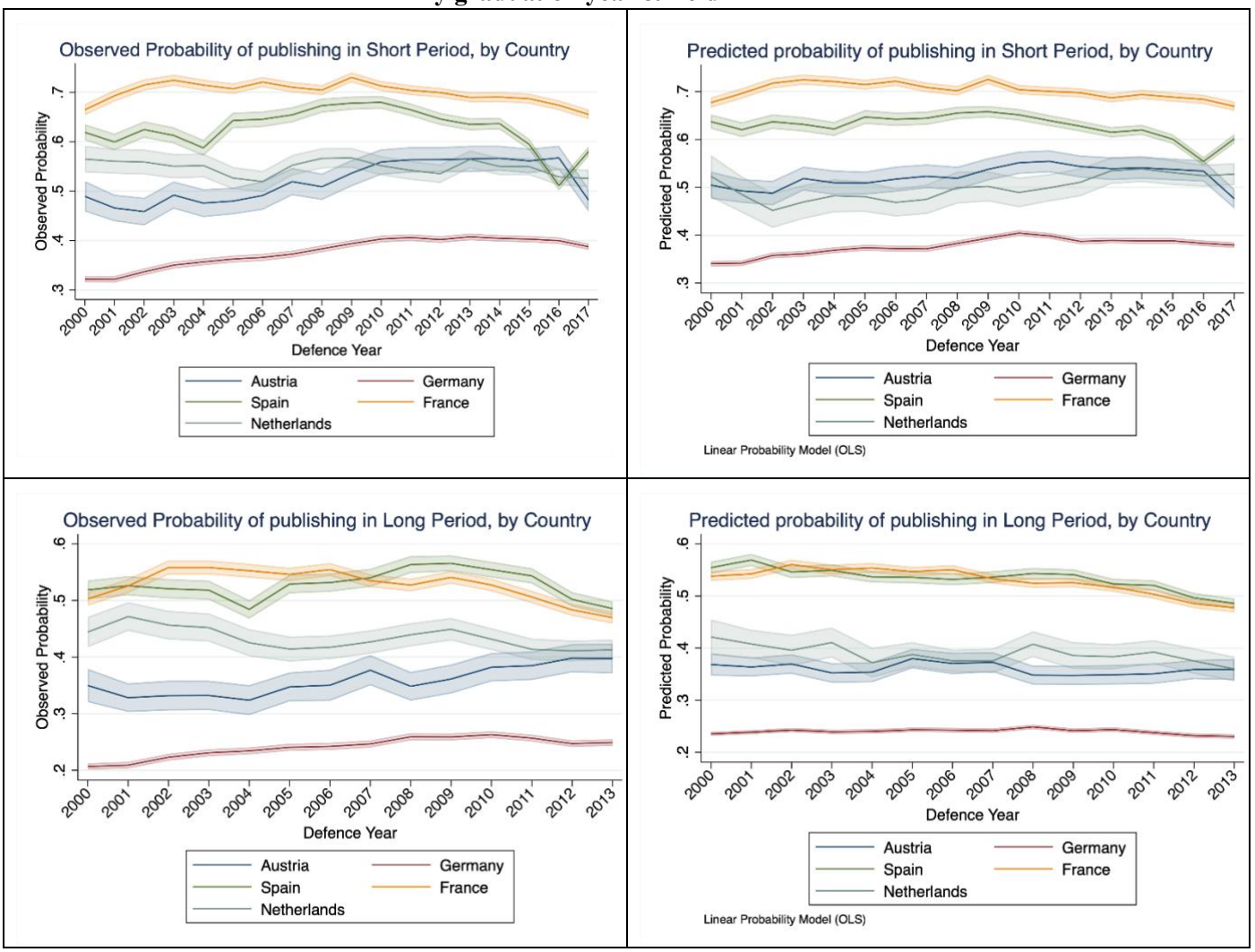


Figure C2: Observed vs predicted probability of publishing shortly and long after the PhD

By graduation year & country

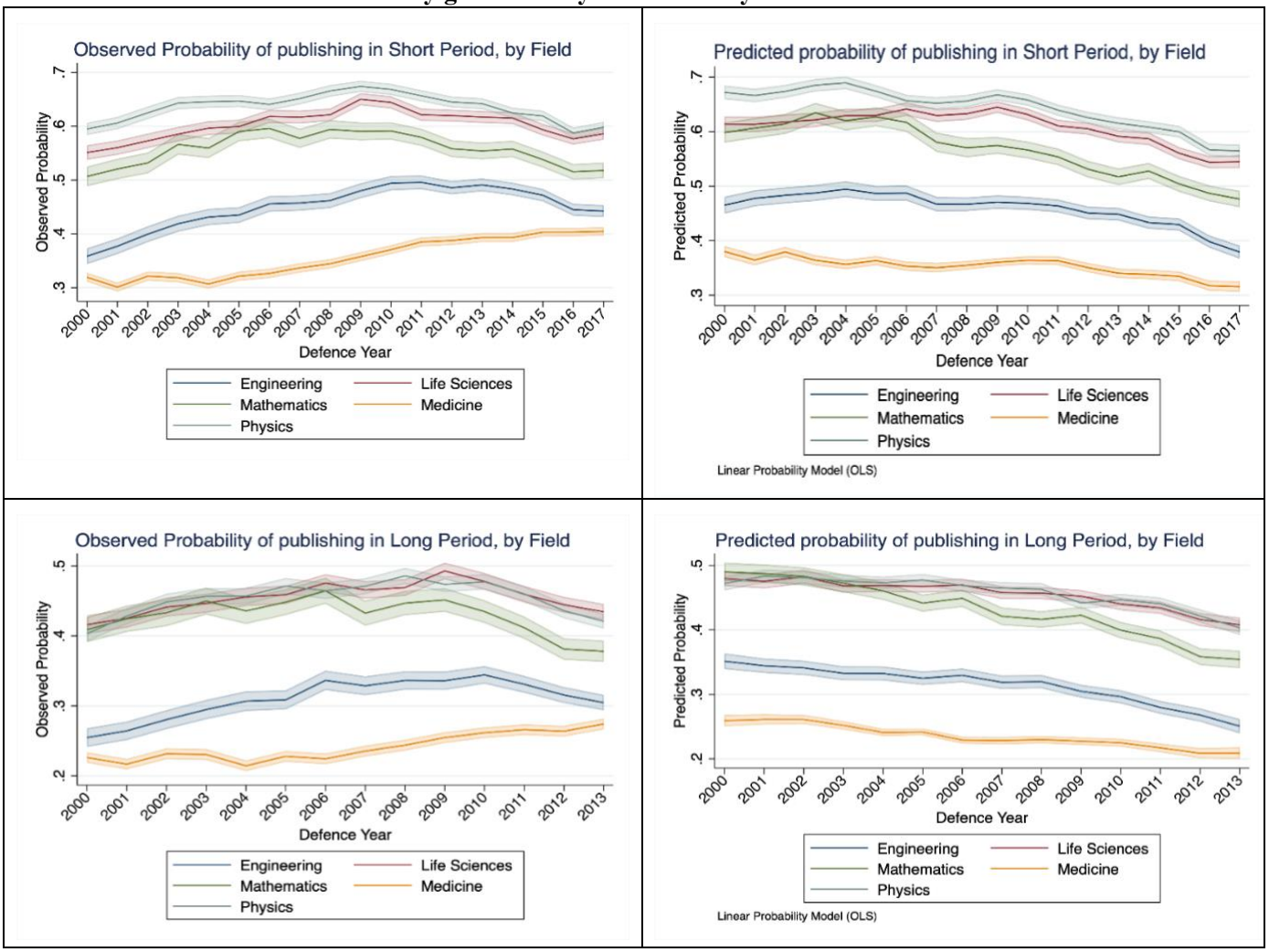
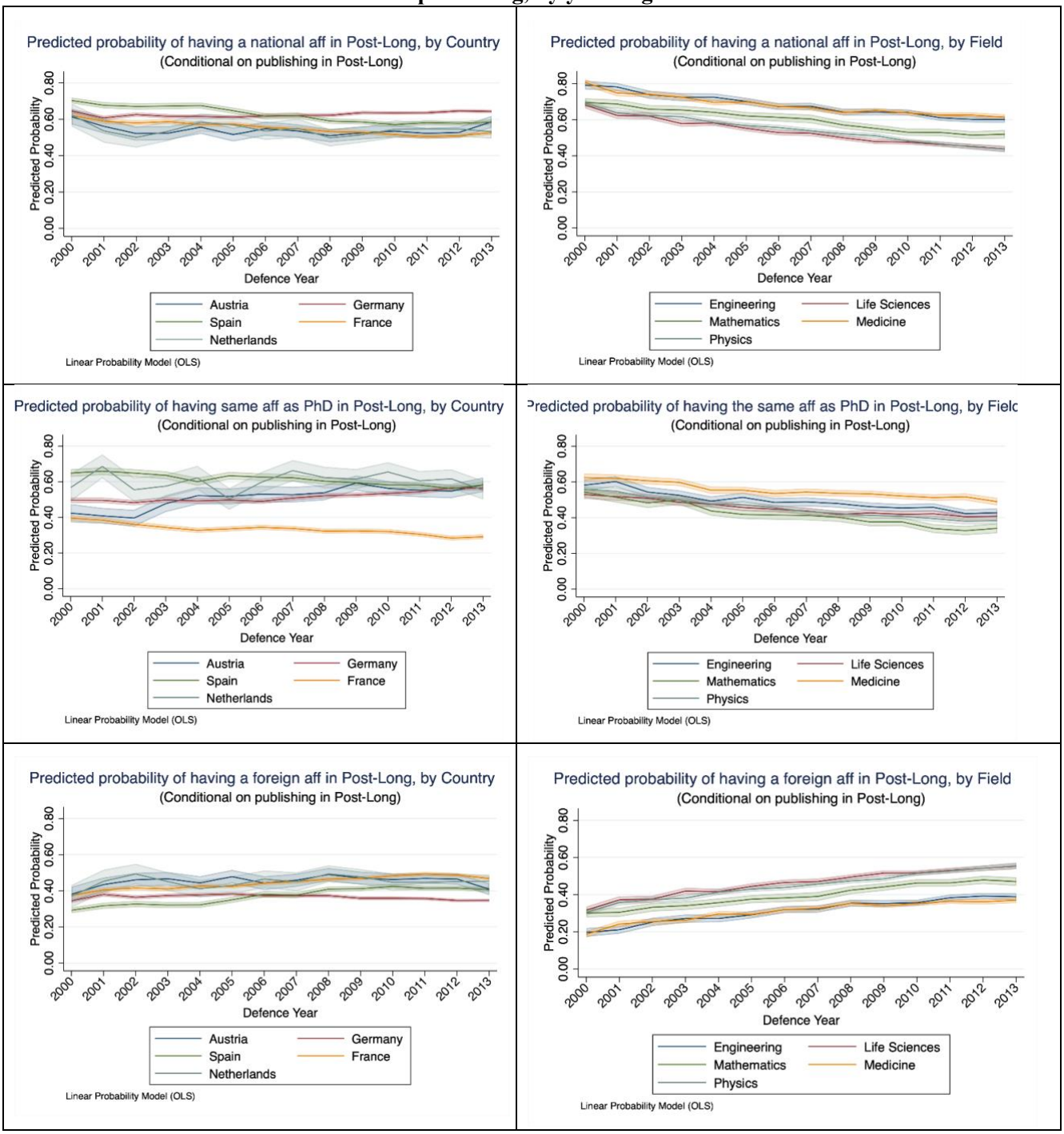
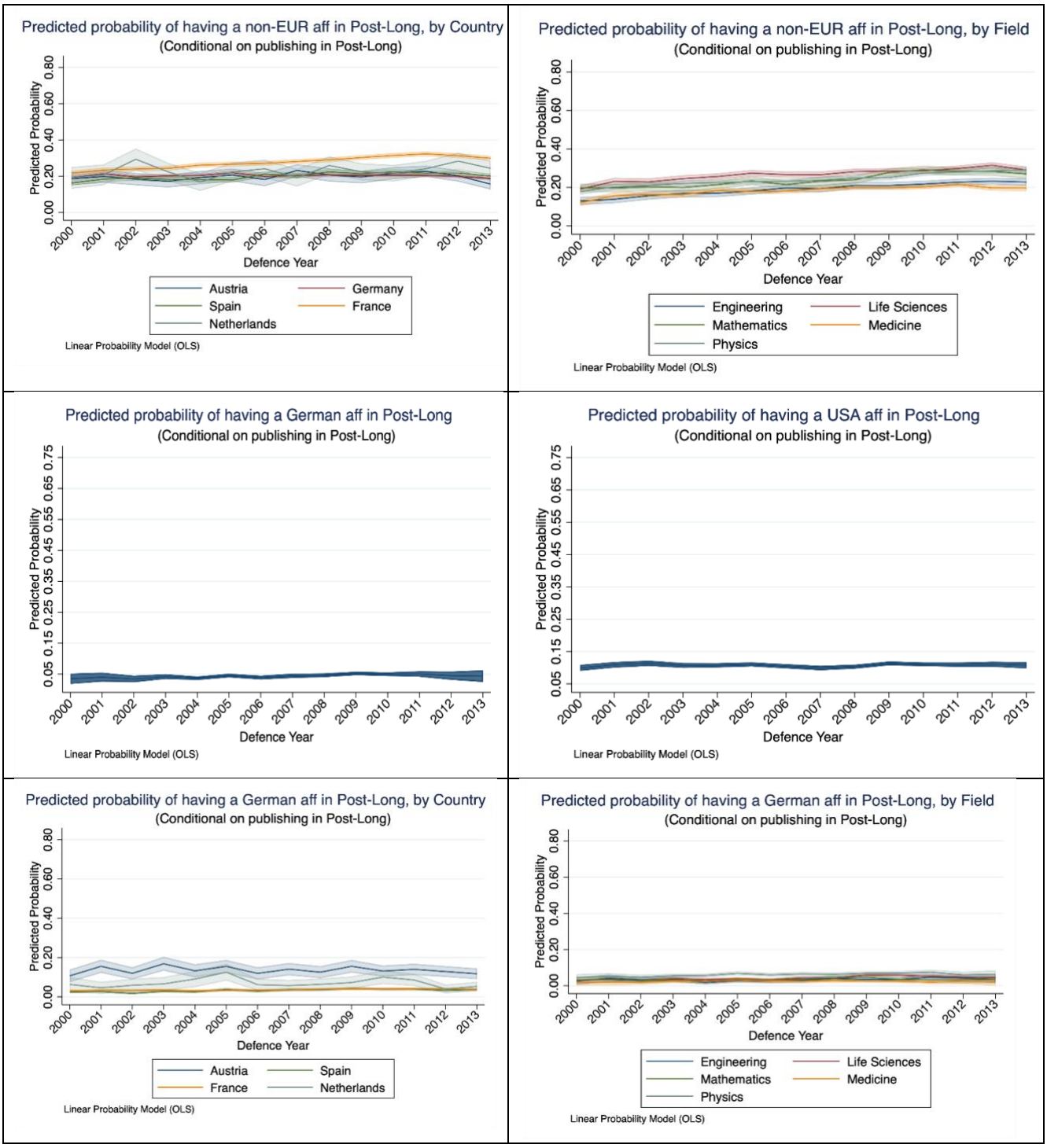


Figure C3: Predicted probability of having national vs foreign affiliations long after the PhD

Conditional on publishing, by year of graduation




Predicted probability of having a non-EUR aff in Post-Long, by Country
(Conditional on publishing in Post-Long)
Predicted Probability
0.00 0.20 0.40 0.60 0.80
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Defence Year
Austria
Germany
Spain
France
Netherlands
Linear Probability Model (OLS)
Predicted probability of having a non-EUR aff in Post-Long, by Field
(Conditional on publishing in Post-Long)
Predicted Probability
0.00 0.20 0.40 0.60 0.80
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Defence Year
Engineering
Life Sciences
Mathematics
Medicine
Physics
Linear Probability Model (OLS)
Predicted probability of having a German aff in Post-Long
(Conditional on publishing in Post-Long)
Predicted Probability
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Defence Year
Linear Probability Model (OLS)
Predicted probability of having a USA aff in Post-Long
(Conditional on publishing in Post-Long)
Predicted Probability
0.05 0.15 0.25 0.35 0.45 0.55 0.65 0.75
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Defence Year
Linear Probability Model (OLS)
Predicted probability of having a German aff in Post-Long, by Country
(Conditional on publishing in Post-Long)
Predicted Probability
0.00 0.20 0.40 0.60 0.80
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Defence Year
Austria
Spain
France
Netherlands
Linear Probability Model (OLS)
Predicted probability of having a German aff in Post-Long, by Field
(Conditional on publishing in Post-Long)
Predicted Probability
0.00 0.20 0.40 0.60 0.80
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Defence Year
Engineering
Life Sciences
Mathematics
Medicine
Physics
Linear Probability Model (OLS)

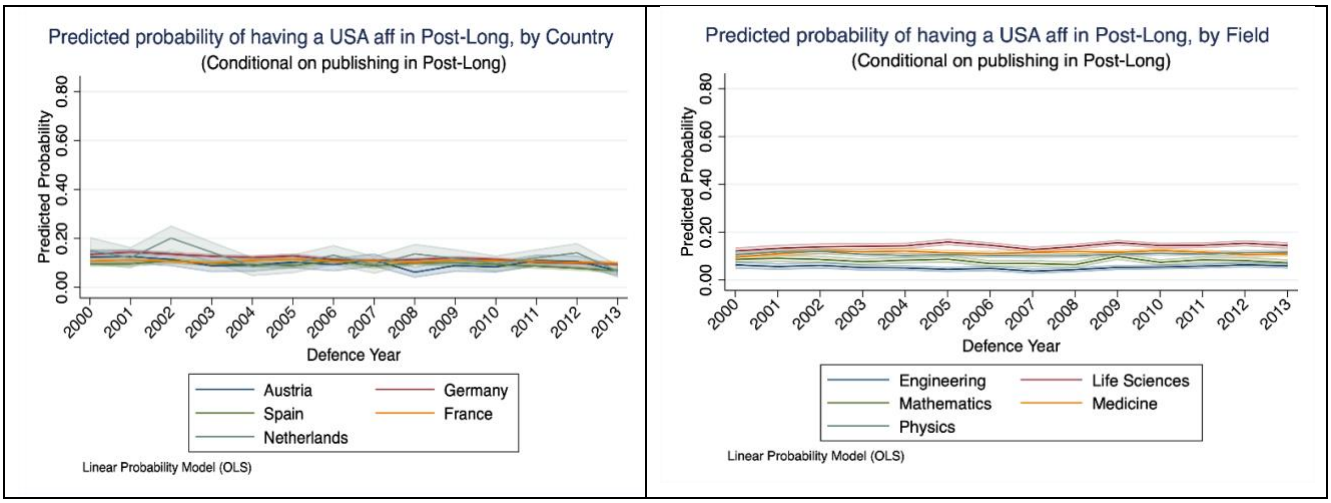


Figure C4: Predicted probability of having a corporate affiliation long after the PhD

Conditional on publishing, by year of graduation

