Off the beaten path: What drives scientists' entry into new fields?

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Abstract

Given that prestige sits at the core of the scientific reward system and that venturing into unknown territory carries substantial risk, scientists don't take the decision to enter a new field lightly. This paper analyses the individual and contextual factors associated with entry into new-to-the-researcher fields of research. Using a panel of researchers in biomedical sciences and engineering from a large European research university, we find that productivity affects new field entry as such, but is not associated with entry into fields that are very distant to one's current expertise. Such 'long jumps' are more likely to be made by talented, rather than merely productive researchers. Scientists in more senior ranks, with larger co-author networks and collaborating with PhD students are more likely to enter fields but these factors don't represent an additional push to enter very remote fields. Finally, accounting for its endogeneity, we find that funding does not make new field entry more likely but, conditional on entry, supports 'long jumps'.

Keywords: economics of science; new field entry; scientific funding

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*"In this age of specialization, men who thoroughly know one field
are often incompetent to discuss another."*

Richard Feynman, Caltech lunch forum, 1956

1 Introduction

Science is known to be a risky endeavour, where payoffs in terms of scientific success can be highly uncertain (Arrow, 1962). Given that ‘wrong turns’ in one research trajectory may have long-lasting consequences, scientists arguably don’t take the decision to enter a new field lightly. These choices define whether they develop a more generalist profile that spans disciplinary boundaries, as opposed to being a specialist in a narrower set of fields and have ramifications for the production of scientific knowledge at an aggregate level.

Our analysis contributes to the literature on the organization of scientific research by addressing the question what drives scientists to enter research fields which are new to them and diversify their research agendas. We use a rich dataset which covers a wide set of influencing factors for researchers across different scientific fields from a leading European research university (KU Leuven, Belgium). The set of determinants we consider ranges from age, gender, tenure and rank, co-authorship teams, over talent, past track record, experience with new field entry to research funding. By taking a comprehensive approach, we complement prior work that has zoomed in on specific fields, like biomedical researchers (Azoulay *et al.*, 2011) or specific factors, like career incentives or teams, as potential explanations for why scientists expand the scope of their research. For example, Franzoni & Rossi-Lamastra (2017) find that tenured scientists are more

likely to diversify their research portfolio and theorize that the associated job security mitigates the risks that come with diversifying into new fields. In a recent study showing evidence of a specific barrier to new field entry, Azoulay *et al.* (2019) find that, following the unexpected deaths of preeminent life scientists, individuals from outside fields are more likely to enter and succeed.

Our framework pays special attention to the role of research funding. Considering funding as a potential driver of research orientation departs from prior work on the impact of funding, which is mostly concerned with its effect on productivity and collaboration (Bozeman & Gaughan, 2007; Goldfarb, 2008; Defazio, Lockett, & Wright, 2009; Auranen & Nieminen, 2010; Jacob & Lefgren, 2011; Grimpe, 2012; Hottenrott & Lawson, 2013; Kelchtermans & Veugelers, 2011, 2013; Whalley & Hicks, 2014; Gush *et al.*, 2015). In one of the few studies on changes in research direction following the acquisition of grants, Azoulay *et al.* (2011) showed that the HHMI program stimulates biomedical scientists to explore new lines of investigation within biomedical research, an effect which can be attributed to the characteristics of the HHMI funding scheme. Myers (2019) finds that it requires a substantial amount of (expected) funding to induce scientists to make even small changes in the direction of their research, indicating that the switching costs are substantial. We seek to contribute to this small but growing empirical literature by establishing whether the receipt of research grants affects new field entry, taking into account its endogeneity. More specifically, in our empirical framework we disentangle whether drivers affect new field entry directly as well as indirectly through their effect on funding. Finally, since not all new field entries are alike in terms of their distance to the scientist's existing expertise and since distance will affect the risk-reward trade-off, we not only analyse them as binary outcomes but also consider

the distance of new field entries and whether they are particularly remote from the scientist's current field(s) of research.

Our unbalanced panel (1992-2001) of 734 KU Leuven researchers in biomedical and exact sciences shows the effects of drivers of new field entry tend to differ depending on whether entry is distant or not. We find in our econometric analysis that high-quality scientists are not more likely to enter new fields *per se*. However, conditional on new field entry, they are more likely to make 'long jumps'. In contrast, scientists' past productivity record is associated with new field entry, but it is not associated with (long) distance, conditional on entry. Researchers' experience with new field entry has little bearing on whether they will repeat that behaviour. Career incentives matter: each successive step in the academic hierarchy provides an additional push to enter new fields, but not distant ones. For research funding, we find that academics are *less* inclined to venture into new research fields if they obtain a grant. Interestingly, the results suggest a dual role, as funding is positively associated with entering very distant fields.

The remainder of the paper is organized as follows. The next section outlines our framework for assessing the risk-reward trade-off that scientists face when they consider entering new fields. Section 3 discusses the data and operationalizes the variables used in the analysis. Section 4 presents the results and robustness checks. Section 5 concludes and reflects on policy implications.

2 Framework for Assessing New Field Entry

Implicitly or deliberately, scientists take into account a multitude of factors when deciding whether to embark on research that branches out into scientific fields they are

less familiar with. To analyse these decisions, we build on the economics of science literature to develop a framework that outlines the risks and rewards associated with new field entry, incorporating individual capacities and preferences, career concerns and incentives stemming from the competitive funding system.

2.1. The Risk-Reward Trade-Off

The scientific reward system is a critical factor that shapes scientists' decisions on which research trajectories to follow. More specifically, with rewards going disproportionately to 'big hits', there's a ruthless competition to win the race for being the first to come up with new and big scientific discoveries. This system may push scientists to take more risk by going into new territory in order to increase their odds to come up with a big hit. At the same time, it might also result in researchers pursuing similar research strategies i.e. *"researchers tend to be drawn into duplicative races"* (Dasgupta & David, 1994, p507). The 'winner takes all'-logic in science may therefore hold back a scientist to enter a new field unless she has strong beliefs that she has a comparative advantage to win the race.

Given that the nature of scientific competition is focused on big wins, how to trade off the rewards and risks when deciding on entering new fields? Analogous to financial portfolio investment, new field entry can be considered a diversification strategy to lower the overall risk of failure. At the same time, diversification into new areas may avoid the diminishing returns from continuing in existing areas and reaching dead ends (Hackett, 2005). Diversification constitutes an even more valuable coping mechanism in more mature fields, where the risk looms larger that a scientist finds herself in an exhausted area of research (Siow, 1998).

Besides limiting the downside risk, another line of reasoning in favour of new field entry is that it increases the 'upside potential' of one's research. A central tenet of the literature

on creative thinking is that creativity requires breaking away from prior experience (Simonton, 1999), allowing for new perspectives that arguably characterize major breakthroughs in science. Wang *et al.* (2018) show how novel science, although entailing higher risk, is more likely to become a big hit. From this perspective, choosing a more novel research trajectory by venturing into new areas may offer the researcher a higher return but comes with a higher risk.

Influencing the risk-reward trade-off when venturing into new areas, is how distant the new areas are from the areas which the researcher is familiar with. Going into new but closely related territories may reduce the risk of failure, but it may also lower the potential rewards - particularly the potential for big rewards - as these may require more, and highly different, areas to be combined. Hence, going into distant new areas may offer even higher rewards, but with commensurate higher risk.

2.2. Factors Shaping the Risk-Reward Trade-Off from Venturing into New Areas

Talent and Productivity Record in Existing Areas of Expertise

The capacity to be creative in science and to deal with its risk-reward trade-off is linked to talent, which David (1994) labelled the “sacred spark”-hypothesis. More talented scientists are better able to generate more novel ideas and be more successful in bringing these novel approaches to a success (Simonton, 2003), particularly when it concerns less obvious novel ideas associated with entering more distant new areas. However, talented researchers also face a higher opportunity cost for venturing into new territories, and past work looking at inventors has shown that successful people tend to generate increasingly incremental ideas (Audia & Goncalo, 2007). In addition, while highly talented researchers may be apt at avoiding the pitfalls associated with entering a new field, even they are not certain that their existing expertise will be transferable to the new

field or that productive cross-fertilization between fields will take place. In other words, the uncertainty associated with new field entry implies a higher risk than remaining on familiar turf.

Scientists will weigh their talent – and the associated capacity to capitalize on new field entry - and their preference for risk against the cost of new field entry. In particular, entering an unfamiliar field comes with an opportunity cost in the form of foregone further specialisation in existing areas of expertise. That cost is arguably non-negligible given the ever-accumulating knowledge that one needs to assimilate in order to stay abreast of the latest findings in one's domain, and which is considered an important reason for the observation of increased specialization in science (Jones, 2009). Furthermore, persistently focussing on a narrow set of topics may not only be needed to acquire the necessary competences, but also to convert accumulated expertise in published results (Hackett, 2005) as well as to establish and defend one's reputation in the field (Cole & Cole, 1967).

In sum, while a scientist's talent and productivity record in his existing areas of expertise arguably play an important role when deciding to enter new fields, it is *ex ante* not clear whether one's talent and productivity record relate positively or negatively to new field entry. Also, the relation with making long jumps is unclear. Talent may allow making bigger jumps, but at the same time a particular concern for 'long jumps' to remote fields is that one's existing expertise will not be as useful in the new field as on more familiar territory.

Experience with New Field Entry

Scientists may be subject to 'path dependence' i.e. a scientist's propensity to enter new fields may depend on her track record of past new field entries, which reflects her

intrinsic preference for exploration, attitude towards risk and ability to bridge fields. In addition, familiarity with a bigger and broader range of scientific fields implies more opportunities to exploit synergies when considering to venture into yet another field. Since there is a limited number of scientific fields someone can reasonably publish in, there may be decreasing marginal returns of new field entry for scientists with a larger stock of past field entries.

Career Incentives & Age

The importance of reputation in science reflects that scientists do not work in a vacuum but are part of an institutional system that provides various (dis)incentives for entering new fields. An important and highly visible feature of the academic organizational context is the hierarchical rank system, in which scientists move up from assistant to full professor. Career concerns constitute an important driver of scientists' behaviour (Dewatripont *et al.*, 1999). As argued above, while it may hold less promise for novel contributions, specialization avoids the uncertainty that comes with new field entry. Hence, it reduces the risk of missed promotions from lack of output. This holds when the promotion process may not be particularly favourable towards risk taking and failure, biasing against new field exploration. Junior scientists may therefore suppress their inclination to explore other scientific fields before they achieve tenure, especially the riskier longer jumps. Franzoni & Rossi-Lamastra (2017) indeed find evidence that tenured scientists are more likely to diversify their research. After securing tenure, and particularly once the full professor rank has been attained, promotion-related concerns no longer at play. Hence, the urge to play-it-safe may diminish and factors like curiosity, the lure of breakthroughs and international visibility and recognition may push full professors more easily into novel research directions, despite the higher risks.

Independently from the incentives stemming from the academic career ladder, the tendency to enter new fields may decline towards the end of the scientist's career. While such life cycle effects have been demonstrated to hold with respect to scientific productivity (Levin & Stephan, 1991), a shortening remaining time horizon in academia may also reduce the appetite to invest in mastering new fields, if one takes into account that the returns from these risky investments may take a long time to materialize.

Teams

Science is increasingly being done in (larger) teams, which has been ascribed to the increasing 'burden of knowledge' and easier long-distance communication (Wuchty *et al.*, 2007; Jones *et al.*, 2008; Jones, 2009; Agrawal *et al.*, 2013). While the scientist's decision to enter a new field is ultimately her own, the team(s) she is part of shape the social context within which she does her work and may exert an important influence. More specifically, co-authors may serve as a steppingstone to enter new fields of research if they act as a conduit to different bodies of knowledge (Lee *et al.*, 2015; Visentin *et al.*, 2017). While they did not consider entry into new fields as such, Ayoubi *et al.* (2017) show the role of teams for scientists' tendency to tap into knowledge that is new to them but known to their team members.

Funding

The incentives stemming from funding schemes may also affect research orientation decisions. More specifically, they may be steered by the competitive awarding of research grants on the basis of bibliometric measures, which has become an institutionalized practice. Geuna (2001) already observed that many European universities had adopted a contractual-oriented approach to funding with an emphasis on research output, which has now become the dominant paradigm for allocating research money (Jonkers &

Zacharewicz, 2016). This evolution has provoked the criticism that competitive funding systems compromise other important values like diversity and novelty of research (Hicks, 2012; Alberts *et al.*, 2014). Gatekeepers of the science system, such as editors of prominent journals, have questioned the effectiveness of a metrics-based approach of research evaluation and funding, claiming that it encourages “me-too science” (Alberts, 2013). Consistent with this view, Wang *et al.* (2016) show that traditional bibliometric indicators such as journal impact factors and short-term citation counts don’t do a good job at capturing the most novel research. The reliance on this type of indicators fuels the perception that funding agencies are risk-averse, selecting relatively safe projects that exploit existing knowledge at the expense of those that explore untested approaches (Alberts, 2013; Walsh, 2013; Stephan *et al.*, 2017). Boudreau *et al.* (2016) indeed found that grant proposals that deviate strongly from evaluators’ expertise have lower chances of being positively evaluated. In other words, to the extent that it is biased towards established track records, the scientific funding system discourages scientists’ entry into new fields.

Conversely, there are also reasons to expect a positive relation between research funding and new field entry. Funding provides researchers with the resources to pursue curiosity-driven research avenues. Particularly if funding is substantial and covers a period of time long enough to provide the researcher with the protective space to tackle ambitious questions and allows sufficient degrees of freedom to reorient the research along the way, it induces researchers to take more risk when branching into new, more distant, research directions (Hollingsworth, 2004; Heinze *et al.*, 2009; Azoulay *et al.*, 2011).

3 Data & Methodology

We use a panel (1992-2001) of 734 professors in biomedical and exact sciences of the KU Leuven.³ KU Leuven is a research-intensive university that is consistently ranked among the top 100 universities in the world in comprehensive university rankings (ARWU/Shanghai and THE).⁴

3.1. Dependent Variable: New Field Entry

We define entry into new scientific fields by constructing an indicator for each researcher with the value 1 for every year a scientist publishes in a field in which she hasn't published before, provided she publishes at least once more in that field in subsequent years.⁵ The latter condition implies that we exclude one-time only excursions into other fields i.e. we require a minimum level of 'stickiness' for new field entries.⁶ Our measure relies on evidence of new field entry evidence through a publication, which excludes new field entry that does not result in a publication record.

To determine new field entries, we use publication data from the Web of Science (WoS) dating back to 1971, which allows tracing the fields in which a scientist has published over the years. The taxonomy of scientific fields is based on the 255 "subject categories" used for classifying each WoS publication, shown in Appendix. We adjusted this classification so it displays a consistent granularity across the entire spectrum of scientific fields.⁷ In particular, some WoS subject categories consist of several sub-categories (e.g. *chemistry* is subdivided in *analytical*, *applied*, *inorganic* and *nuclear chemistry*), while others do not (e.g. *microbiology* is not further subdivided). The resulting classification of 194 fields cover all domains of science, including social sciences and arts & humanities. Given our sample of biomedical and exact scientists, the 129 scientific

fields covering the domains of science and engineering account for the bulk of publication activity in our sample. The full list of fields is included in Table A1 in Appendix.

In order to test for any differences depending on how distant the newly entered field is (conditional on entry), we consider two additional dependent variables. First, we consider the *distance* of a scientist's main field (i.e. in which she has the most publications to date) to the newly entered field(s). To construct this variable, we first calculate the yearly cosine similarity matrix between fields based on cross-citations between journals, using their respective WoS subject categories (Zhang *et al.*, 2010; Stephan *et al.*, 2017).⁸ The distance between each pair of fields is then defined as 1 minus the similarity score. Closer fields will have a smaller distance score, fields that don't cite each other have a distance equal to one. The dependent variable is calculated as the distance between the researcher's main field and the newly entered field, again conditional on the entry being 'sticky'.⁹ We further leverage the distance measure by analysing the probability of 'long jumps' relative to one's main field, defined as those field entries that are more than 1 standard deviation away from one's main field, taking into account all new field entries in the sample in the same year.

The yearly average number of scientific fields a researcher publishes in in our sample is 4,4, which is very similar to numbers reported in other studies. For example, Franzoni & Rossi-Lamastra (2017) rely on semantic clustering of article titles and abstracts and find that scientists publish on average in 4,1 "research themes" per year. With respect to *new field entry*, 486 out of the 734 researchers in our sample, i.e. 66%, enter a new scientific field at least once in the considered period (1992-2001) and at the scientist*year level about 22% of observations correspond to new field entries (see the 'Entry in new field' column, bottom row, in Table 1). Conditional on entering a new field, scientists enter on

average 1,54 new fields per year. accounting for a mean distance of 0,92 with a small standard deviation.¹⁰ On average about 13% of new entries are “large jumps”, with a large standard deviation of 0,34. Table 1 further shows that new field entry patterns differ substantially across disciplines. Scientists in *Biology* and *General & Internal Medicine* are most likely to enter a new field, while *Mathematics* displays the lowest probability of new field entry but – conditional on entry – the latter shows a higher prevalence of long jumps.¹¹

[Table 1 about here]

As the number of new field entries for a researcher in a given year is smaller than two, we don't estimate a count model but rather focus on the probability of new field entry in a given year, and conditional on entry, we estimate the distance from one's main field and the probability of making a long jump.

The estimation sample for the probability of new field entries has 734 researchers traced over from 1992 till 2001, leaving a sample of 4,706 observations. The estimation sample for distance and long jumps includes only those observations in which a new field entry is observed, leaving 1,022 observations (N= 486).

3.2. Covariates

In this section we operationalize the framework discussed in section 2. We report descriptive statistics for the different covariates used in our empirical analysis in Table 2.

[Table 2 about here]

Talent and Productivity

As a proxy for talent, we include a pre-sample measure of a scientist's research quality by looking at his average number of citations per publication before 1992 relative to the average number of citations per publication in the scientist's main discipline in the entire Web of Science in 1991. The average value is 0,97 but with a standard deviation of 1,06. Researchers whose pre-sample publication quality is above, respectively below, the world average do not seem to differ materially in terms of their new field entry decisions (see the right panel of Table 2).

In addition, we compare each scientist's publication output in every year to her colleagues in the university who are active in the same main discipline.¹² Using k-means clustering, we classify researchers each year into one of three mutually exclusive clusters (low, medium and high).¹³ About 13% of our sample observations are in the high productivity cluster. Membership of a high productivity cluster is associated with a higher likelihood of new field entry.

Experience with New Field Entry

To capture a scientist's experience with new field entry, we include the stock of unique scientific fields in which the researcher has been active up to that point. Besides a scientist's inclination to diversify into new areas, this variable also captures the potential for synergies of a new field entry with the scientist's existing scope of expertise. Sample researchers are on average active in 9 fields. Table 2 shows no apparent link between the

size of a researcher's stock of fields relative to peers in her discipline and the propensity to enter additional fields, although scientists with an above-median stock of fields seem more likely to make long jumps. We also look at the spread of a scientist's publications across fields by calculating the Herfindahl concentration index, with 1 denoting full specialization in a single field. Also, splitting the sample by the median shows no major differences in field entry behaviour, apart from a slightly higher occurrence of long jumps for the less specialized scientists.

Career Incentives & Age

Incentives and risks stemming from promotion perspectives are captured by a scientist's rank, for which we distinguish between assistant professor, associate professor, professor and full professor. Slightly over one quarter of researcher*year observations (28%) fall into the assistant professor group. Note that for the university that we study, tenure coincides with the promotion to associate professor, so we do not include a separate control for tenure. The yearly share of researchers entering a new field is fairly constant across ranks, while the appetite for making long jumps increases with rank.

The average seniority (i.e. years since starting employment at the university), is about 10 years. Consistent with their smaller publication track record, the junior faculty are more prone to enter new fields. Conversely, long jumps are more prevalent among the more senior scientists.

Teams

We measure the size of a scientist's network of co-authors by counting all unique co-authors of a researcher on all his publications in a given year, both including internal and external (i.e. non-KU Leuven) co-authors. The average annual team size is 13,9 with a

large standard deviation (20,0). These relatively high numbers are driven by lab-based disciplines like *Biosciences* (26,6) and *Clinical and Experimental Medicine* (22,9).¹⁴ To assess whether especially co-authors from other disciplines may promote new field entry, we include the percentage of co-authors that share their main discipline with the focal researcher. On average, 41% of co-authors are active in the same main field as the focal researcher. We also include the number of PhD students that graduate in a given year and who were supervised by the focal scientist. Doctoral students may act as ‘scouts’ for the supervisor in terms of exploring novel ideas that break into other fields. Table 2 shows that researchers with above-median sized teams and numbers of PhD students are more likely to enter new fields. Supervision of more PhD students is positively associated with making long jumps as well as, somewhat surprisingly, smaller teams and teams with higher shares of co-authors in the same main discipline.

Funding

The funding scheme we observe is the Research Fund of the KU Leuven (known as “BOF”), which represents a quarter of all research funding available to researchers at the university. The fund is financed by the Flemish government and its overall size is determined by the share of the KU Leuven in the output of scientific publications and citations in the Flemish region. The university manages the fund autonomously through a competitive process involving external peer reviewers. In the observation period, the funding scheme contained two major funding programs, open to applicants across the whole university and accepting proposals that are entirely driven by the curiosity of the scientist. In other words, the studied funding programs are ‘neutral’ with respect to new field entry as they do not a priori steer researchers in a certain direction. Of the pre-screened applications that are allowed to submit a full proposal less than 50% obtains

funding. Grants vary between 475,000 Euro for individual researchers or small teams up till 1,625,000 Euro for larger teams, with funding periods from four to five years. As such, this funding scheme, with its bottom-up nature, large budgets and long time windows should allow for a protective space to enter new research areas.

In our sample, 42% of researchers receive a BOF grant at least once in 1992-2001 (Table 2). Funding is positively correlated with entry into new fields, with 1 out of 4 researchers who have received a BOF grant entering new fields, compared to 1 out of 5 for non-funded researchers, and also more likely to make long jumps. Table 3 compares funded and non-funded researchers and shows that they differ systematically in terms of their characteristics. Funded scholars have a significantly higher pre-1992 quality of research, with a normalized citation rate of 1,23 versus 0,86. They are also twice as likely to be in the high productivity cluster (22% versus only 11% of unfunded researchers). Funded researchers are more often found among the higher (tenured) ranks and more senior scientists.

Receiving a BOF grant also varies substantially by discipline (not shown in the table). For example, bioscientists have the highest funding rate at 54% i.e. more than half is funded at least once in the sample period, compared to only 16% of mathematicians. The annual co-author network of funded researchers is on average more than twice the size compared to colleagues without BOF grants, and with a higher share of co-authors from the same main discipline.

[Table 3 about here]

As funded scientists differ systematically from unfunded scientists, not only in terms of new field entry, but also in terms of the covariates, we need to take selection effects into account to identify the true effect of funding on new field entry. Funding might go primarily to those scientists who are more inclined to enter new fields anyway. Further, factors like talent, track record and career stage are not only drivers of new field entry (cf *supra*), but also increase the likelihood of receiving funding. Therefore, besides a single equation model, we estimate a 2-stage linear probability model in which we account for the probability to receive funding in the first stage, using an instrumental variable approach.¹⁵ As an individual-specific instrument, we use the receipt of funding by the number of university colleagues who share the same discipline with the focal scientist and who obtained funding in the same scheme (BOF) in the corresponding year. The rationale is that one's own probability of being funded is correlated with the number of peers who are successful in acquiring funding in the same funding scheme (BOF). On the other hand, colleagues' success in acquiring funding is unlikely to affect any new field entries by the focal researcher, making this a valid instrument.¹⁶

Besides addressing the endogeneity of funding, estimating a separate funding equation further allows decomposing the effect of the covariates into a direct and indirect effect on new field entry. More specifically, we can disentangle whether the drivers of new field entry as discussed in our framework (talent, productivity, experience with new field entry, career incentives) operate indirectly through funding (1st stage) and/or whether they affect new field entry directly (2nd stage).

We lag the covariates in both the funding and the field entry equation by one year to mitigate endogeneity arising from simultaneity. For the funding variables, we use a two-year lag to account for the time it takes before a grant translates into published results.

We have tested the robustness of our results using different lags of funding and obtain very similar results for longer lags.¹⁷

3.3. Control variables

Given that some fields may serve more easily as a steppingstone to enter additional fields (see Table 1), we control for a scientist's past experience by including dummy variables for each **scientific field** in which the scientist published in the past. The highly granular classification of 193 fields provides an individualized 'map' for each scientist. In a robustness check, we control for a scientist's main discipline (using the more aggregate classification discussed in section 3.1), defined as the one in which she has the majority of her publications, based on her lifetime publication record. This more general classification saves on degrees of freedom at the cost of not fully capturing all field specificities. It also restricts the analysis of distance, as it ignores the distance between subfields within the aggregate discipline, which is where most of the new field entry takes place. The findings for this alternative specification are robust to the main results using the more granular field fixed effects, as we report in section 4 below.

In addition, we control for a number of individual characteristics. Although male and female scientists seem equally likely to enter new fields (Table 2), we control for **gender** in the multivariate analysis. We also include an indicator for whether a professor was part of the **post-1992 entry cohort** to capture a spike in hiring at the university in that year. This variable also corrects for the fact that we have less observations to calculate stocks for the most recent entrants in the sample. We control for whether a scientist is working **full-time** at the university. The effect of a part-time position could go both ways with respect to new field entry, as it may capture limited time for research but also connections to another set of colleagues, if combined with an affiliation at another

institution. While the descriptive statistics in Table 2 do not suggest a major role for teaching, academics with higher **teaching loads** (measured as the average number of teaching hours per week) and consequently restricted research time may have weaker incentives to enter new fields. A correlation table including all covariates is included in Table A2 in Appendix.

4. Results

Table 4 shows our econometric results for the 3 dependent variables i.e. new field entry (0/1) and, conditional on entry, the distance to the newly entered field and the occurrence of ‘long jumps’. In general, significance levels for results on distance are weak, hampered by a lack of sufficient heterogeneity, as the low standard deviation reported in Table 1 shows. For results on distance, we primarily rely on the results for the “long jumps”: although they are less frequent than field entries as such, there is more heterogeneity to be exploited (see Table 1). We first discuss the results in the single equation entry models before we turn to the discussion of the 2-stage linear probability models, in which we account for the probability to receive funding in the first stage.

[Table 4 about here]

Talent and productivity. While talent, as measured by the ratio of one’s citations per publication relative to the world average, does not seem to be significantly more associated with new field entry (see model 1 in Table 4), one’s past productivity record, as measured by belonging to the medium or high productivity cohort in the previous year, shows a significant positive relation with the likelihood of new field entry.¹⁸ The role of

quality and productivity differs once we consider how far the newly entered field is from the researcher's current expertise, conditional on new field entry (see models 2 & 3). Contrary to new field entry as such, the researcher's quality is positively associated with distance, in particular with the probability of making long jumps (0.027, significant at the 5% level). For the researchers who make new field entries, the more productive ones don't appear more likely to enter more distant fields.

Experience with new field entry. A researcher's stock of new field entries is negatively associated with additional entry (model 1), supporting diminishing returns to new field entry and diversification. Perhaps even more surprising, is that, conditional on new field entry, experience with new field entry does not help to make "long jumps", on the contrary: the larger the stock of new field entries in the past, the less likely "long jumps" are being made (model 3), suggesting a diminishing tendency to new field entry. However, there is no significant evidence that, conditional on a researcher's stock of fields, more specialization - as measured by higher values for the Herfindahl index - explains whether she would enter additional fields.¹⁹ Also in the distance and 'long jump' models we do not find a significant effect for specialization within a given scope of fields covered.

Career incentives & age. Career age (seniority) is negatively associated with new field entry: older researchers are significantly less likely to enter new fields. However, conditional on seniority, the higher ranks are increasingly associated with new field entry compared to assistant professors (model 1). So incentives for entering new fields operate throughout the career hierarchy, with not only tenure (which coincides with the associate professor rank in the data) but also having reached higher steps on the career ladder providing an additional push to take on the risk of entering a new field and full professors

the most likely to enter new fields.²⁰ Conditional on entry, career age nor rank is associated with the distance of entries or the probability to make “long jumps” i.e. the appetite for risk of the higher ranks seems constrained to new field entry as such without providing a further nudge to venture into more distant fields (models 2 & 3).

Teams. Researchers with a higher number of co-authors are more likely to enter new fields and the same holds for researchers who supervise more doctoral students (model 1). However, the number and relatedness of one's co-authors do not have an effect beyond the entry decision as such. Conversely, the effect of PhD students persists: supervising more doctoral students is not only associated with new field entry but also with entering more distant fields (model 2). This suggests that PhD students perform a 'scouting role' for the scientist, exploring avenues that are more remote from her main research. There is a limit however: in the long jump model PhD students no longer show a significant positive effect.

Funding. Looking first at the single equation results (models 1-3), shows that funding positively affects the likelihood of new field entry, but not significantly. Conditional on new field entry, although affecting distance negatively (but not significantly), funding does show a significant positive association with making long jumps. Accounting for its endogeneity, with the instrument being highly significant (see models 4a-5a-6a), funding shows a negative but again insignificant coefficient (model 4b). Further, conditional on entry, funding shows a negative association with the distance of newly entered fields ($\beta = -0.116$, significant at the 10% level). Interestingly, the sign changes when we consider 'long jumps': funding is positively associated with long jumps with a large and significant coefficient ($\beta = 0.499$, significant at the 5% level). In sum, the pattern that emerges is that funding does not make scientists more 'adventurous': if anything, it makes them less

likely to go into new fields or enter more distant fields. But the results suggest a dual role in the sense that funding is positively associated with entering very distant fields.

The 2-stage estimation procedure also allows comparing the effects of covariates, disentangling direct effects from effects running indirectly through funding, taking into account their effect on likelihood to get funded. The 1st stage results in models 4a-5a-6a show which covariates are significant for selection into funding (model 4a for the total sample, relevant for the 2nd stage results on new field entry in model 4b; models 5a and 6a for the subsample of new field entry observations, relevant for the 2nd stage results on distance and long jumps in models 5b and 6b). These 1st stage results show not unexpectedly the importance of talent and productivity for the selection into funding (although only significantly in the full sample), but also a positive association with the career stage and team size variables and, interestingly, a negative association with the stock of new field entries (especially for new field entry as such, model 4a). All else equal, funding seems to bias against scientists who have a larger stock of entered scientific fields.

In general, taking into account selection into funding, and with funding not significantly affecting new field entry (if properly instrumented), the 2nd stage results for the covariates do not change sign or significance for new field entry, suggesting that the total effects of the covariates are mostly direct. But the positive career rank effects are much stronger in the 2nd stage results than in the single equation model, indicating that for these covariates the direct positive association with new field entry is dampened by their indirect effect through funding.

Taking into account the selection into funding is more important for the covariates' effects on "long jumps". Comparing the single equation and 2nd stage 2SLS results shows

that the overall negative significant stock of fields effects from the single-equation analysis disappear in the 2nd stage results, indicating it is entirely due to the indirect effect running through funding.

Controls. The field fixed effects are important controls, stressing that the scientific context matters. Also, their granularity matters: in particular the result for stock of fields is sensitive to using fixed effects at the level of the fine-grained set of scientific fields rather compared to the 12 broader disciplines.²¹

Other controls, like gender or teaching load are not significant. A noteworthy observation is that the cohort that entered the university in or after 1992 on average stays closer to fields they are familiar with (as opposed to the older cohort) but they are more likely to make long jumps than their colleagues who have been at the university longer. Finally, when adding individual fixed effects as controls, many control variables become insignificant, as there is no or too little variance across time per researcher.

4 Conclusions

In the economics of science literature, a lot of attention has gone to a better understanding of scientific productivity. Although undoubtedly very informative for policy makers, output is only one product of the scientific process. This paper shifts the focus to the direction that scientists' research agendas take, looking at what drives scientists to enter research fields which are new to them. Using a unique dataset from a leading European research university, we study the risk-reward trade-off associated with entering new and distant fields based on a framework encompassing both individual and contextual characteristics, including talent, productivity in one's main field,

specialization, experience with new field entry, career stage, seniority, team structure and funding .

The results show that entry into new fields is quite common. About two thirds of researchers in our sample go into a new field at least once in a 10-year period. Both the likelihood of entering a new field and, conditional on new field entry, the likelihood of making a “long jump” vary substantially within our sample. The econometric analysis first of all shows that individual characteristics matter for explaining new field entry. While for new field entry a scientist’s past productivity record plays a role rather than research quality, it is quality and not productivity that makes long jumps significantly more likely. Our results are consistent with diminishing returns to new field entry, as researchers with more experience in new field entry are significantly less likely to make additional new field entries and are especially less likely to make long jumps.

Second, the analysis shows that context matters. The career stage of a scientist has implications for how risk and rewards are traded off, with full professors most likely to enter new fields, although not when it comes to making “long jumps”. Also, the size of one’s scientific network of co-authors and working with PhD students matter for entering new fields. Finally, when properly taking into account the selection into funding, we find no evidence in our sample that funding serves as a mechanism to venture into new territory. However, conditional on entry, funded researchers are more likely to make long jumps. Our results also show that the negative selection into funding of researchers with experience in new fields, fully accounts for their lower likelihood to make long jumps. Once correcting for this selection, profiles with larger stocks of new field entry are no longer significantly less likely to make “long jumps”. In sum, pivotal changes in working context and when they occur in scientists’ careers have an effect on how their research

agendas develop and whether a given scientist over time spans many disciplinary boundaries or rather specializes deeply in a few fields. At the level of the aggregate science system such individual decisions accumulate and result in a particular composition of specialists and generalists, and varying degrees thereof in various fields.

Many of the contextual factors we identified can be influenced through policy and perhaps the primary policy lever for influencing research orientation that emerges from our analysis is funding. To the extent that society wants scientists to come up with novel findings and that these are primarily found by spanning fields, our results suggest that the funding system seems to perform poorly on average with respect to inducing researchers to enter new fields, although it does seem to foster long jumps. This result ties into the debate on science funding with prominent scientists calling into question the design of funding mechanisms that reflect funders' risk-aversion and bias against more risky, novel scientific endeavours (Lane, 2009). Furthermore, funding agencies like to advertise the success of their support for science, but many fail to provide hard evidence on the causal effects of their grants (Gush *et al.*, 2015). To the extent that policy makers aim to increase diversity of research, our findings show that competitive grant schemes may not have the desired effects, leading scientists to specialise and capitalize on their past research experience.

Our analysis is limited by the available data, which suggests several avenues for further research. One obvious restriction is limited heterogeneity since we analyse one university and a limited set of research grants, aimed at basic research. Hence our results cannot be readily generalized across institutions and different funding schemes. As the work of Azoulay *et al.* (2011) suggests, the precise characteristics of the funding program matter in terms of shaping the precise incentives, with sizeable, long-term, people-

focused funding creating a context that is more favourable to developing novel research questions.²² Also the source of funding plays a role, with prior work showing that industry funding may shift academic research agendas from basic towards more applied science (Florida & Cohen, 1999; Gulbrandsen & Smeby, 2005; Glenna *et al.*, 2011; Banal-Estañol *et al.*, 2015). Therefore, an extension of our analysis could consider a wider variety of funding schemes in order to better understand the effects of design choices. Further analysis on a wider sample would also allow to look into more detail on the effects of team size and composition on the decisions to enter new and distant fields.

To assess the impact of individual entry decisions, follow-up work could consider more explicitly the interaction between diversification and scientific performance i.e. how productive scientists are after new field entry, and how likely larger “jumps” are to produce publications that are outliers in terms of impact. Prior studies that have looked at technological and scientific search as a process of recombination have found that the value of new combinations of knowledge components is not higher on average, but does show higher variability i.e. there is not only a higher chance of breakthroughs but also of duds (Fleming, 2001; Wang *et al.*, 2016). Hence, it would be interesting to ascertain whether scientists are able to make high-impact contributions in newly entered fields and whether this impact is primarily recognized (cited) in the ‘old’ or ‘new’ field.

5 References

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6 Tables

Table 1: New field entry (averages across researchers and years, by main discipline)

	Entry in new field (0/1)		Number of new fields ^Δ		Distance to new field ^{†Δ}		Long jumps (0/1) ^Δ	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Agriculture	0,25	0,43	1,65	0,99	0,94	0,07	0,26	0,44
Biosciences	0,23	0,42	1,52	0,80	0,89	0,09	0,02	0,15
Chemistry	0,16	0,37	1,46	0,80	0,95	0,08	0,25	0,43
Engineering	0,18	0,39	1,54	0,97	0,97	0,06	0,36	0,48
Geosciences	0,21	0,41	1,55	0,74	0,95	0,08	0,23	0,43
Mathematics	0,09	0,29	1,65	0,70	0,99	0,01	0,47	0,51
General & internal medicine	0,29	0,46	1,67	1,05	0,89	0,08	0,03	0,18
Non-internal medicine ^{††}	0,23	0,42	1,51	0,94	0,93	0,07	0,09	0,28
Neuroscience	0,11	0,32	1,10	0,32	0,92	0,07	0,00	0,00
Physics	0,17	0,37	1,21	0,60	0,96	0,05	0,32	0,47
Biomedical	0,18	0,39	1,66	0,97	0,89	0,07	0,03	0,19
Biology	0,29	0,45	1,53	0,81	0,89	0,08	0,07	0,26
All disciplines	0,22	0,41	1,54	0,94	0,92	0,08	0,13	0,34
[†] Distance between researcher's main field prior to year t and the newly entered field. Maximum distance in case multiple fields were entered in a single year.								
^{††} E.g. dermatology, ophtalmology, otolaryngology, dentistry...								
^Δ Conditional on new field entry.								

Table 2: Descriptive statistics (yearly averages across researchers, N=734)

			Entry (0/1)	Nr of fields	Distance	Long jump (0/1)
Variable	mean	s.d.	mean	mean	mean	mean
Talent and productivity						
Quality _{pre-1992} (citation rate vs world avg)	0,97	1,06				
≥ 1 (above world average)	1,88	1,23	0,23	1,52	0,92	0,14
< 1 (below world average)	0,43	0,33	0,21	1,55	0,92	0,13
Productivity cluster						
Low	0,52	0,38	0,16	1,49	0,92	0,13
Medium	0,34	0,31	0,26	1,55	0,92	0,13
High	0,13	0,26	0,31	1,60	0,92	0,14
Experience with new field entry						
Stock of fields (#)	8,97	6,21				
≥ median [†]	12,60	6,61	0,22	1,53	0,93	0,15
< median [†]	4,99	3,26	0,21	1,55	0,91	0,10
Herfindahl index of stock of fields	0,33	0,23				
≥ median [†]	0,46	0,24	0,22	1,51	0,92	0,11
< median [†]	0,19	0,09	0,21	1,55	0,93	0,15
Career Incentives & Age						
Rank						
Assistant professor	0,28	0,40	0,22	1,55	0,91	0,09
Associate professor	0,25	0,34	0,21	1,52	0,91	0,10
Professor	0,21	0,34	0,21	1,52	0,93	0,16
Full professor	0,25	0,41	0,23	1,55	0,94	0,17
Seniority (years)	10,33	7,67				
≥ median [†]	15,41	6,85	0,19	1,53	0,94	0,17
< median [†]	4,16	2,00	0,25	1,54	0,91	0,10
Teams						
Co-authors (#)	13,92	20,00				
≥ median [†]	25,40	34,19	0,27	1,55	0,92	0,12
< median [†]	2,74	3,52	0,17	1,51	0,92	0,15
Co-authors in same discipline (%)	0,41	0,31				
≥ median [†]	0,56	0,41	0,22	1,52	0,92	0,15
< median [†]	0,13	0,18	0,22	1,58	0,92	0,10
PhD graduates (#)	0,36	0,53				
≥ median [†]	1,53	0,93	0,27	1,55	0,94	0,17
< median [†]	0,00	0,00	0,20	1,52	0,91	0,09
Funding (0/1)						
Funded*	0,42	0,49	0,26	1,56	0,92	0,15
Unfunded	0,58	0,49	0,20	1,53	0,92	0,12
Controls						
Teaching load (hours/week)	3,99	3,78				
≥ median [†]	7,36	3,96	0,21	1,55	0,93	0,14
< median [†]	1,56	1,31	0,23	1,53	0,91	0,12
Male (1/0)	0,91	0,29	0,22	1,54	0,92	0,13
Female (1/0)	0,09	0,29	0,23	1,49	0,91	0,16
Post-1992 entry cohort (1/0)	0,45	0,50	0,25	1,60	0,90	0,12
Full-time employment (1/0)	0,91	0,27	0,22	1,53	0,92	0,13

* *Funded* = 1 if the researcher ever had a BOF grant in 1992-2001.

[†] The median is relative to other researchers in the same main discipline.

Table 3: Comparison of funded and unfunded researchers

Variable	Funded mean	Unfunded mean	t-statistic	p-value
Talent and productivity				
Quality _{pre-1992} (citation rate vs world avg)	1,23	0,86	11,08	0,00
Productivity cluster				
Low	0,32	0,60	-18,75	0,00
Medium	0,47	0,29	11,93	0,00
High	0,22	0,11	10,07	0,00
Experience with new field entry				
Stock of fields (#)	11,53	8,38	15,40	0,00
Herfindahl index of stock of fields	0,28	0,34	-8,39	0,00
Career Incentives & Age				
Rank				
Assistant professor (%)	6,29	25,37	-15,56	0,00
Associate professor (%)	23,32	28,43	-3,63	0,00
Professor (%)	26,82	22,87	2,91	0,00
Full professor (%)	43,58	23,33	14,28	0,00
Seniority (years)	11,60	9,77	7,58	0,00
Teams				
Co-authors (#)	23,14	11,15	14,20	0,00
Co-authors in same discipline (%)	51,47	37,46	10,98	0,00
PhD graduates (#)	0,71	0,31	14,11	0,00
Controls				
Teaching load (hours/week)	4,66	4,39	2,05	0,04
Male (1/0)	0,93	0,90	2,73	0,01
Post-1992 entry cohort (1/0)	0,23	0,39	-10,32	0,00
Full-time employment (1/0)	0,98	0,91	9,21	0,00

Table 4: Regression results for new field entry

	Single equation models			Two-stage models					
	New field entry model 1	Distance model 2	Long jump model 3	1st stage (funding)			2nd stage (entry)		
				New field entry model 4a	Distance model 5a	Long jump model 6a	New field entry model 4b	Distance model 5b	Long jump model 6b
Talent & Productivity									
Quality _{pre-1992}	-0,007 (0,006)	0,003 (0,002)	0,034*** (0,011)	0,024*** (0,009)	0,019 (0,017)	0,019 (0,017)	-0,002 (0,007)	0,005* (0,003)	0,027** (0,013)
Medium productivity group _{t-1} [†]	0,070*** (0,016)	0 (0,006)	-0,037 (0,024)	0,050*** (0,016)	0,033 (0,030)	0,033 (0,030)	0,080*** (0,018)	0,003 (0,007)	-0,048* (0,026)
High productivity group _{t-1} [†]	0,070*** (0,024)	0,013 (0,009)	-0,027 (0,036)	0,031 (0,027)	0,001 (0,048)	0,001 (0,048)	0,074*** (0,025)	0,011 (0,010)	-0,021 (0,037)
Experience with new field entry									
Stock of fields	-0,191** (0,089)	-0,025 (0,015)	-0,315*** (0,114)	-0,107** (0,052)	-0,135* (0,073)	-0,135* (0,073)	-0,071* (0,038)	-0,016 (0,018)	0,083 (0,073)
Herfindahl index of fields	0,035 (0,036)	0,009 (0,018)	0,059 (0,078)	-0,06 (0,046)	-0,007 (0,093)	-0,007 (0,093)	0,021 (0,038)	0,008 (0,018)	0,06 (0,085)
Career Incentives & Age									
Rank ^{††}									
Associate professor	0,029 (0,022)	-0,006 (0,009)	0,028 (0,032)	0,087*** (0,027)	0,150*** (0,045)	0,150*** (0,045)	0,055** (0,028)	0,014 (0,015)	-0,052 (0,052)
Professor	0,060** (0,027)	-0,002 (0,011)	0,033 (0,036)	0,177*** (0,038)	0,163*** (0,061)	0,163*** (0,061)	0,106*** (0,040)	0,02 (0,018)	-0,057 (0,064)
Full professor	0,109*** (0,037)	-0,006 (0,016)	0,054 (0,053)	0,260*** (0,049)	0,218*** (0,081)	0,218*** (0,081)	0,173*** (0,057)	0,021 (0,022)	-0,054 (0,082)
Seniority	-0,008*** (0,001)	0 (0,001)	0,003 (0,002)	-0,003 (0,002)	-0,005 (0,004)	-0,005 (0,004)	-0,009*** (0,001)	0 (0,001)	0,004 (0,003)
Teams									
Co-authors	0,001*** (0,000)	0 (0,000)	0 (0,000)	0,001* (0,000)	0,001 (0,001)	0,001 (0,001)	0,001*** (0,000)	0 (0,000)	0 (0,000)
Co-authors in same discipline	-0,018 (0,017)	-0,005 (0,008)	-0,003 (0,028)	0,052** (0,021)	0,014 (0,041)	0,014 (0,041)	-0,006 (0,019)	-0,003 (0,008)	-0,009 (0,030)
PhD graduates	0,019** (0,009)	0,005* (0,003)	-0,001 (0,017)	0,044*** (0,010)	0,033** (0,016)	0,033** (0,016)	0,029** (0,011)	0,008** (0,003)	-0,014 (0,019)
Peers who acquired funding_{t-2}									
				0,420*** (0,072)	0,395*** (0,123)	0,395*** (0,123)			
Funding_{t-2}									
	0,019 (0,019)	-0,006 (0,007)	0,061** (0,028)				-0,21 (0,148)	-0,116* (0,068)	0,499** (0,234)
Controls									
Teaching load	-0,001 (0,002)	0,001 (0,001)	0,002 (0,005)	-0,010*** (0,003)	-0,008 (0,006)	-0,008 (0,006)	-0,003 (0,003)	0 (0,001)	0,006 (0,006)
Male	-0,013 (0,025)	-0,001 (0,011)	-0,047 (0,039)	-0,005 (0,032)	0,008 (0,051)	0,008 (0,051)	-0,017 (0,026)	-0,001 (0,012)	-0,046 (0,042)
Post-1992 entry cohort	0,036 (0,022)	-0,022** (0,008)	0,083*** (0,030)	-0,041 (0,033)	-0,116** (0,054)	-0,116** (0,054)	0,032 (0,023)	-0,030*** (0,010)	0,118*** (0,043)
Full-time position at the university	-0,014 (0,029)	-0,004 (0,011)	-0,016 (0,048)	0,090*** (0,031)	0,117** (0,057)	0,117** (0,057)	0,004 (0,031)	0,008 (0,014)	-0,065 (0,059)
Field fixed effects	<i>included</i>	<i>included</i>	<i>included</i>	<i>included</i>	<i>included</i>	<i>included</i>	<i>included</i>	<i>included</i>	<i>included</i>
Observations	4,706	1,022	1,022	4,706	1,022	1,022	4,706	1,022	1,022
Researchers	734	486	486	734	486	486	734	486	486

***, **, and * indicate significance levels of 1%, 5% and 10%, respectively. Robust standard errors (clustered by researcher) in parentheses. All models include an intercept.

[†] The reference category is the low productivity group. ^{††} The reference category is assistant professor.

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² The findings, interpretations and conclusions expressed in this paper are entirely those of the authors and should not be attributed to the European Commission. Possible errors and omissions are those of the authors and theirs only.

³ The data comprises the population of professors in biomedical and exact sciences employed by KU Leuven in 1992-2001. We only use the 734 scientists who publish at least once in that period, resulting in 4,706 observations. For these active scientists we constructed full publication and citation records (including their publications before 1992) from the Web of Science (WoS, Clarivate Analytics). In order to retrieve each researcher's publication history, we performed searches on scientists' names (last name and first initial of the first name, as registered in personnel records) and, to avoid false matches due to homonyms, affiliation. For the latter, we used the *Organization-Enhanced* field provided by Clarivate Analytics, which links all possible variations of an organization's name found in the Web of Science. We also added the search term "University Hospital Leuven" to ensure all publications by clinical scientists affiliated to the university's medical departments were included in the data. The retrieved publications are restricted to those on which the scientists mention their KU Leuven affiliation. Although this may imply incomplete coverage of publication records, mobility of researchers is known to be very limited in our sample, especially in the time period we consider.

⁴ <https://www.kuleuven.be/english/research/>

⁵ We consider the following types of publications: "Article", "Article; Book Chapter", "Article; Proceedings Paper", "Letter", "Meeting Abstract", "Note", "Proceedings Paper", "Review".

⁶ This restriction also partially addresses the concern that a field entry may be linked to co-authorships with colleagues whose main expertise is in fields that are new to the focal scientist. Also here, repeated publications in that field (even with the same team of co-authors) mitigates the concern that the focal scientist merely supplies own expertise without having much exposure to the new field.

⁷ The Web of Science classifies every journal and book that the *Core Collection* covers in "subject categories". To distinguish them from the simplified categorization that underlies our analysis, we use the term "scientific field" throughout the paper for any of the 194 fields. We also use a more aggregate journal-based classification of 12 broad "disciplines", developed by the Centre for Research & Development Monitoring (ECOOM, KU Leuven), shown in Table 1.

⁸ For example, the most similar scientific fields in 1992 were '*Remote Sensing*' and '*Imaging Science & Photo Technology*', with a cosine similarity value of 0.692. The least similar in the same year (with a non-zero cosine value) are '*Astronomy & Astrophysics*' and '*Biochemistry & Molecular Biology*'. In 2002, '*Cell Biology*' and '*Biochemistry & Molecular Biology*' were the most similar, while '*Astronomy & Astrophysics*' and '*Health Policy & Services*' were the farthest apart of all fields.

⁹ In case the researcher enters more than 1 field in a year, we take the maximum distance between the researcher's main field and all of the entered fields.

¹⁰ The high mean value for distance (i.e. close to 1) reflects the on average low cross-citations between journals from the 194 different fields, resulting in an average pairwise cosine similarity of 0,02. Related fields do show higher cosine similarity values, e.g. *Cell & Tissue Engineering* and *Transplantation* (0,11) or *Genetics & Heredity* and *Biochemistry and Molecular Biology* (0,57).

¹¹ Note that some disciplines account for a fairly small number of scientists. The smallest disciplines in the sample are *Neuroscience* (12 scientists), *Geosciences* (18) and *Mathematics* (25). The average number of scientists per discipline is 61.

¹² For the list of main disciplines, see Table 1.

¹³ Robustness checks using different numbers of clusters in prior work (Kelchtermans & Veugelers, 2013) showed that researchers cluster into 3 distinct productivity groups with the average numbers of publications of the 3 clusters being statistically significantly different. If the researcher published in more than 1 of the 12 disciplines in a year, we classify her based on the highest cluster performance.

¹⁴ These splits by discipline are not reported in Table 2 but are available from the authors.

¹⁵ To the best of our knowledge, there is no implementation of estimators that fully accommodates a dependent and endogenous variable that are both binary, with the exception of special regressor methods (Lewbel *et al.*, 2012). Because the requirements for the special regressor cannot be fulfilled by any variables in our data, we estimate a linear probability model (LPM) through 2SLS. It has been noted in the literature

that LPM-based estimates of coefficients in binary choice models are consistent (e.g. Claussen *et al.*, 2015) and provide good approximations of true marginal effects, even if they do not fit choice probabilities perfectly (Angrist & Pischke, 2009). A LPM may underestimate standard errors, which is why the results should be interpreted with some caution. However, statistical significance levels of the covariates in the new field entry equation are consistent with those of the estimates of a logit model (the latter without the endogeneity correction of funding). Moreover, the consistency of the results of using a binary DV and the distance to new fields provides additional reassurance of the robustness of the results.

¹⁶ Note that the treatment effect of funding on new field entry that is estimated in the 2nd stage may still capture unrevealed intentions of new field entry by scientists in the grant application stage. For example, a scientist may not disclose her intentions to enter a new field in the grant proposal (e.g. if she believes this will decrease her chances of getting funding) but may nevertheless decide to enter a new field after she wins the grant. To the extent that the selection equation cannot control for this strategic behavior of the scientist, the analysis would show a spurious positive relation between funding and new field entry. However, funded researchers must submit ex-post reports on what they did (not) execute so we assume that they do what was promised in the grant proposal. In addition, we control in the selection equation for the researcher's stock of fields, which captures her appetite for new field entry.

¹⁷ The only noteworthy difference is when we use a shorter 1-year lag for the funding variable, in which case we no longer obtain a statistically significant estimate for the funding variable. We attribute this to the time it takes before acquired funding translates into publications that reflect potential new field entry.

¹⁸ Given that quality is measured as the average citation rate of a scientist's pre-sample (=before 1992) papers, it is necessarily more noisy for the cohort that entered the university in or after 1992 since for assistant professors (which is the starting rank for the vast majority of those who enter the university) the measure will be based on a limited number of publications. A robustness check (not reported) splitting the cohort that entered before 1992 from the one that entered in or after 1992 shows that the results for quality (but also productivity) are indeed mainly driven by the pre-1992 entry cohort, with these characteristics positively and highly significantly associated with the entry into new fields.

¹⁹ In a robustness check where we add researcher fixed effects, the stock of fields is negatively linked to the acquisition of funding but there is no longer a significant relation with new field entry. In the individual fixed effects model, we also find that the more concentrated one's portfolio of past fields (*Herfindahl index of fields*), the more likely new field entry becomes. In other words, once we control for the inherent taste for new field entry, researchers with more specialized expertise seem more conducive to leverage it in new fields.

²⁰ Wald tests for pairwise comparisons of the coefficients for associate professor ($\beta = 0.055$), professor ($\beta = 0.106$) and full professor ($\beta = 0.173$) show they are significantly different at the 5% level.

²¹ A scientist's stock of fields is negatively and significantly associated with new field entry in the model with field fixed effects while it is positive and significant in the model with discipline fixed effects (for both the single equation model and the 2nd stage IV regression). This difference suggests that it is primarily the past entry in specific fields that explains additional new field entry.

²² The BOF funding system that we analyze is an open competition across fields with each proposal assessed by two external referees and the university research council. While we cannot rule out that the effects are contingent on specific features of this funding scheme, it does reflect the principles of other systems that competitively allocate research grants.

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