

Gender and Academic Mobility

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ABSTRACT. What explains the gender gap in academic careers? This paper studies how geographic mobility constraints contribute to gender disparities in academic hiring, using novel administrative data covering the universe of PhD graduates in France (2009-2021) across all academic fields. I link individuals to the full set of job openings in their field to analyze job search behavior and the probability of obtaining a first academic job. First, I show that both men and women apply to positions that are within a shorter distance to their PhD university, but that women are more sensitive to distance. Second, I leverage quasi-random variation in the geographic structure of the job market across fields and cohorts to show that when available jobs are farther away, applications and hiring fall, especially for women. Finally, I quantify the role of mobility constraints in the hiring gap: when evaluated at the same average market distance, women’s stronger sensitivity to distance lowers their probability of obtaining a first academic job in their first year of application by 1.7 percentage points relative to men, representing about 20% of the average hiring rate. Taken together, the findings highlight geographic mobility constraints as a meaningful and previously underexplored mechanism contributing to gender disparities in academic careers.

Keywords: Geographic Mobility, Academic Career, and Gender Inequality

JEL: I23, J16, J24

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1 Introduction

Women now account for nearly half of all PhD graduates in Europe and the United States. Yet they remain persistently underrepresented among university faculty (She Figures 2021; NSF, 2023). Understanding why women “leak” from the academic pipeline is central not only for equity but also for efficiency. Academic careers are among the most selective and skill-intensive in the labor market, and losing female talent represents a large cost for both scientific diversity¹ and society. Why do these gender gaps persist?

A large literature has explored why women progress more slowly through academic careers. On the demand side, studies document hiring discrimination (Bagues et al., 2017), recognition gaps in citation (Koffi, 2025) and peer evaluation (Sarsons, 2017; Card et al., 2022), and unequal access to professional networks (Ductor et al., 2023). On the supply side, women face hostile work environments (Dupas et al., 2026; Wu, 2018), slower publication processes (Hengel, 2022), and strong family-related constraints (Kleven et al., 2019; Lassen and Ivandić, 2024).

However, this literature has underexplored an important feature of academic labor markets: the need for geographic mobility. Mobility is often a prerequisite of academic careers. In many countries, tenure-track positions are scarce and geographically dispersed, forcing early-career researchers to apply broadly and relocate, sometimes multiple times. Women may face higher mobility costs due to family ties, dual-career constraints, or preferences for proximity (Le Barbanchon et al., 2021). As a result, women may apply to positions that are within a shorter distance, reducing their job opportunities and therefore face a lower chance of obtaining a permanent academic position.

In this paper, I provide new evidence on how geographic mobility shapes gender differences in academic careers, using a unique combination of administrative, bibliometric, and geographic data covering the universe of PhD graduates in France and the universe of applications to academic jobs. I begin by documenting systematic gender differences in first-job search behavior: both men and women apply to positions that are within a shorter distance to their PhD university, but women are more sensitive to distance. I then examine how these mobility constraints contribute to gender gaps in hiring. Using quasi-random variation in the average distance to job openings across disciplines and years, I show that women are more negatively affected by markets where openings are farther away. Finally, I use a back-of-the-envelope calculation to quantify how differences in distance sensitivity contribute to the gender gap in hiring.

¹Dossi (2024) shows that when smaller groups are underrepresented among researchers, this affects both the topics studied and the way research is conducted.

Studying how job search behavior shapes academic careers across disciplines is empirically challenging. In most countries, the academic labor market is decentralized, and existing studies typically observe hiring outcomes but not the full set of applications submitted by candidates. In contrast to other segments of the labor market - where job platforms or centralized registries sometimes capture application flows - academic systems rarely provide systematic information on where candidates apply or how geographically constrained their search is. The French institutional context offers a unique setting to overcome these challenges. Recruitment into permanent university positions follows a centralized and highly transparent process. After completing a PhD, candidates must first obtain a national qualification to become eligible to apply for permanent junior faculty positions (*Maitre de Conférences*)². Between the PhD and the first permanent job, candidates typically hold fixed-term academic positions, including postdoctoral fellowships and temporary teaching or research positions that are not observed in these data. Once qualified, candidates apply simultaneously to vacancies posted by universities across France, making geographic scope a key dimension of early-career search.

I construct a novel dataset that links three rich administrative sources: (i) the universe of doctoral theses defended in French universities (theses.fr); (ii) bibliometric data from Scopus, which I use to measure individual research productivity; and (iii) application and qualification records from the Conseil National des Universités (CNU), which track eligibility, applications, and recruitment outcomes between 2009 and 2021. The application data cover the universe of applications to standard permanent junior faculty openings in France; they exclude applications to foreign jobs and do not track exits from the French academic market. This dataset allows me to track candidates' application behavior and hiring in the French market for permanent junior faculty positions, link them to productivity, and characterize job search strategies in space. Because my analysis focuses on geographic mobility within the French academic labor market, I restrict the sample to individuals who obtained their PhD in France and received the national qualification required to apply for these jobs.

I proceed in three parts. In the first part of the paper, I examine gender differences in job search behavior using a dyadic design that links each PhD graduate to the full set of academic job openings in their discipline and year. I construct a candidate-job-level dataset to estimate how spatial distance affects the likelihood of applying to a given position and whether women are more sensitive to distance than men. This approach allows me to move beyond aggregate patterns and isolate how mobility constraints shape individual job search strategies, conditional on a rich set of fixed effects at the discipline,

²Permanent entry-level university faculty positions in France, broadly comparable to associate professorships.

cohort, university, and individual levels. I find that candidates of both genders are less likely to apply to geographically distant positions, but that the effect is significantly stronger for women. These gendered distance effects are especially pronounced among older candidates and those with weaker publication records.

In the second part of the paper, I examine how mobility constraints contribute to gender gaps in hiring. While the first part documents gender gaps in application patterns, it remains unclear whether these gaps translate into lower success rates for women, or whether women apply more selectively but equally effectively. To address this, I leverage quasi-random variation in the average distance between candidates' PhD university and available job openings across disciplines and cohorts. Using this variation in geographic composition of opportunities candidates face, I show that candidates facing more distant openings are less likely to apply and less likely to secure a position overall. This effect is particularly pronounced for women, suggesting that mobility constraints play a role in shaping gender disparities in early academic placement. To distinguish between the decision to enter the market and the intensity of applications conditional on entry, I estimate the effect of average market distance on two samples: the full sample of qualified candidates and the subsample of qualified candidates who submit at least one application. The results suggest that geographic distance affects application behavior mainly through the extensive margin. Distance significantly reduces the likelihood of applying at all, especially among women, but has little detectable relationship with the number of applications submitted among candidates who do apply. Consistent with this mechanism, a greater average distance is also associated with a lower probability of securing a position, with a larger estimated penalty for women.

To test whether these patterns reflect differences in employer behavior rather than candidate-side selection, I follow [Le Barbanchon et al. \(2021\)](#) and analyze hiring outcomes conditional on application. Using candidate-job-level data, I find that hiring probabilities decline with distance for both men and women. Although the marginal effect is slightly smaller for women, the difference is small and only marginally significant. This suggests that, conditional on applying, women are not penalized more than men based on geographic distance. Instead, the gender gap appears to arise primarily from differences in application behavior.

In the third part of the paper, I provide a back-of-the-envelope quantification of the role of mobility constraints in gender gaps in hiring. Using the reduced-form estimates, I find that women's stronger sensitivity to distance is associated with a 1.7 percentage point lower probability of securing a position relative to men, when both are evaluated at the same average market distance. This magnitude represents approximately 20% of

the average hiring rate in the sample.

Related Literature This paper contributes to three strands of the literature on gender disparities in academic careers. A long-standing literature has documented women’s persistent underrepresentation in academic careers, especially in STEM fields. [Ginther and Kahn \(2004\)](#) shows that women in economics face slower career progression, while [Ceci \(2011, 2014\)](#) and [Meyer et al. \(2015\)](#) emphasize both supply- and demand-side explanations. [Huang \(2020\)](#) provides cross-country evidence that gender disparities in scientific careers remain substantial despite near parity at entry. [Bisantis et al. \(2026\)](#) offers a comprehensive analysis of gender differences in post-PhD academic trajectories using data on the full population of PhD graduates in France since 1988. They document persistent gaps in publication output across all fields and different stages of the academic career, even after controlling for field, cohort, and PhD university, and estimate that nearly 5,700 women are “missing” from academic careers over 25 years. My contribution complements this work by zooming in on the initial transition from PhD to first permanent academic placement, identifying when and how women’s careers begin to diverge from men’s in a centralized and transparent academic system.

Several studies highlight disparities at specific stages of the academic career. [Bosquet et al. \(2019\)](#) shows that women are less likely to be promoted within French economics departments. [Sarsons \(2017\)](#) and [Card et al. \(2022\)](#) demonstrate gender gaps in recognition for co-authored work and peer evaluation, while [Gaule and Piacentini \(2018\)](#) and [Lerchenmueller and Sorenson \(2018\)](#) examine how advisors and early publication trajectories shape career outcomes. In France, [Corsini et al. \(2022\)](#) analyzes PhD students’ productivity, and [Patsali et al. \(2024\)](#) studies research independence. Other work has pointed to structural frictions: [Bagues et al. \(2017\)](#) documents hiring discrimination, [Ductor et al. \(2023\)](#) shows network disadvantages, [Hengel \(2022\)](#) highlights longer review times for female-authored papers, and [Wu \(2018\)](#) and [Dupas et al. \(2026\)](#) document hostile work environments. My paper complements this literature by showing that gender gaps appear already at the transition into the first permanent job, with the final hiring stage accounting for most of the disadvantage.

A growing literature emphasizes the role of family responsibilities in shaping careers. [Kleven et al. \(2019\)](#) show that childbirth generates large and persistent earnings penalties; in academia, [Antecol et al. \(2018\)](#) find that parental leave policies affect tenure outcomes, and [Lassen and Ivandić \(2024\)](#) and [Galván and Tenenbaum \(2026\)](#) document long-run penalties to mothers’ careers. These family constraints are closely related to geographic mobility. [Le Barbanchon et al. \(2021\)](#) shows that women in the labor market often trade off lower wages for shorter commutes. While their analysis focuses on private-

sector workers in France, my paper draws a parallel with a different population: French PhD graduates navigating the academic labor market. Few studies provide systematic evidence on geographic mobility in academic job search. This paper is among the first to do so, showing that women apply to narrower and closer job sets, and that these mobility constraints help explain why women are less likely to secure permanent academic positions.

The remainder of this paper is organized as follows. Section 2 provides context on the French academic system. Section 3 describes the data sources and presents descriptive statistics. In Section 4, I document gender differences in application behavior and mobility. Section 5 documents the impact of application intensity on hiring outcomes. Section 6 concludes.

2 Institutional Context: The French Academic Pipeline

This section provides the institutional background to understand the structure of academic careers in France and how individuals progress from PhD completion to permanent positions. I first describe the organization of the French academic system, including the main ranks and recruitment procedures. I then present the structure of the academic pipeline, which outlines the key transitions from PhD graduation to permanent employment. The final part of the section summarizes three empirical facts that motivate the next stage of the analysis.

2.1 The French Academic System

This section describes how the French academic system works and presents the main stages from the PhD to a permanent position. The French system is highly structured, with national rules that apply to all universities. This organization makes it an ideal setting to study academic careers and gender differences in access to permanent positions. I first describe the two main faculty ranks that define academic careers, and then outline the steps leading from PhD graduation to a permanent junior position.

Faculty ranks and structure

University teachers and researchers in France are civil servants. There are two main ranks: *Maître de Conférences* (MCF), a junior permanent position, and *Professeur des Universités* (PR), the senior rank. The MCF is the first tenured position in a university, comparable to an assistant professor. The PR rank comes later through promotion and is similar to a full professor. Both combine teaching and research duties, with national

rules for pay scales and promotion. The MCF rank therefore, represents the main entry point into a permanent academic career. This paper focuses on the transitions leading to that position. For clarity, I will refer to MCF positions as *junior permanent positions* throughout the paper.

From PhD to national qualification

After completing a PhD, candidates who wish to pursue an academic career must obtain a national *qualification* delivered by the National Council of the Universities (*Conseil National des Universités - CNU*)³. This step confirms that the person is eligible to apply for junior permanent positions. Applications are submitted online and include a CV, a list of publications, teaching experience, and other academic activities. The CNU dossier requires evidence of research activity (e.g., working papers, manuscripts, conference papers, or publications). Candidates apply for qualification either in the months around the PhD defense or in the subsequent years, while holding temporary academic positions (postdoctoral fellowships and teaching or research contracts). Because the application records begin at the qualification stage, I do not observe candidates' intermediate positions prior to qualification. Each discipline has its own CNU committee that reviews applications. The qualification is valid for four years, and candidates may apply in more than one disciplinary section (see Table B10 in the Appendix for an overview). Success rates range between 70 and 90% in most disciplines,⁴ suggesting that this stage is not very selective.

From qualification to MCF recruitment

Once qualified, candidates can apply for junior permanent positions through the national online platform *Galaxie*⁵. All openings are published at the same time each spring, and candidates may apply to several universities. Each university establishes a selection committee composed of both internal and external members. Committees review applications, shortlist candidates, and conduct interviews. The process, therefore, combines national coordination with local autonomy. Junior permanent positions offer civil servant status, an annual teaching load equivalent to 128 lecture hours, research independence within a department, and job security. Promotion opportunities and salary progressions are uniform across universities, which limits within-rank inequality and facilitates comparisons across disciplines. About half of all qualified researchers never

³In rare cases, individuals from abroad may apply for university positions without the qualification, but this exception is uncommon. In practice, the qualification is almost always required to access junior permanent positions.

⁴The rate is around 50% in Law and Political Science due to a more restrictive selection policy.

⁵Starting spring 2026, the platform will change, now called *Odyssée*.

apply on the platform *Galaxie*, reflecting exits from the French academic job market or applications to jobs outside the scope of my records (e.g., abroad or other tracks).

Beyond the junior rank: Promotion and senior ranks

This paper focuses on the early stages of an academic career, up to the first permanent position. Later in the career, promotion to the senior rank, *Professeur des Universités* (PR), requires an additional qualification called the *Habilitation à Diriger des Recherches* (HDR). The HDR certifies that a researcher can supervise PhD students and lead research projects. Promotion to a senior position follows a process similar to the earlier qualification and recruitment stages, with some institutional changes introduced in 2018. [Bosquet et al. \(2019\)](#) studies gender differences in the transition from junior to senior positions within the French academic system in Economics.

Alternative research careers in France

Some researchers in France work in national research organizations such as the *Centre National de la Recherche Scientifique* (CNRS). These positions focus mainly on research and usually do not include teaching. They are fewer in number and very competitive, but they offer an alternative to university careers⁶.

2.2 French Academic Pipeline

This section describes the main stages of the French academic pipeline, from PhD completion to securing a permanent position (see Figure 1). The pipeline is structured around four key transition points that determine career progression and can be divided into two main stages.

Stage 1 covers the period from PhD graduation to obtaining the national qualification, which is required to apply for permanent junior positions. This stage includes two steps: (a) the decision to apply for the qualification and (b) the success of that application. *Stage 2* runs from qualification to securing a junior permanent position. It also includes two steps: (a) applying for a permanent position and (b) the outcome of the recruitment process.

⁶In Economics and related fields, some institutions have also introduced tenure-track *Assistant Professor* positions that lead to a tenured post equivalent to the senior permanent rank, *Professeur des Universités*.

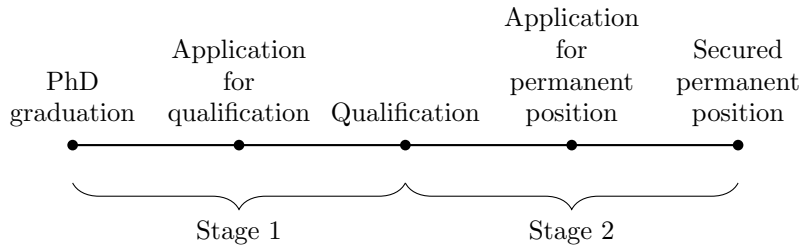


Figure 1: Key transition points

To analyze gender gaps at each transition stage of the academic pipeline, I rely on results developed in a companion paper [Bisantis \(2026\)](#). That work separates the overall probability of securing a permanent position into two components: (1) the probability of obtaining the national qualification, and (2) the probability of being hired into a junior permanent position once qualified. I briefly summarize the main findings here in Facts 1 and 2 to motivate the analysis of underlying mechanisms. The method is detailed in Section ?? in Appendix.

Fact 1: There is a gender gap in access to permanent academic positions

[Bisantis \(2026\)](#) documents systematic gender differences in academic career progression. Across all fields, women are less likely than men to obtain a junior permanent position after completing their PhD. This disadvantage appears at multiple stages of the pipeline but is especially pronounced in the transition from qualification to recruitment into junior permanent positions. In Table A of this paper, columns (5) and (6) show that, in our sample, after controlling for individual characteristics and field-university-year fixed effects, women are about 0.5 percentage points less likely to secure such positions. Given a baseline success rate of 8.6% (column 4), this represents a 6% relative gap.

Fact 2: The gap is driven by application behavior rather than success once applying

Using the decomposition approach, [Bisantis \(2026\)](#) quantifies how each transition contributes to the overall gender gap. The analysis shows that the main source of this gap lies in application behavior rather than in selection once candidates apply: Women and men have similar success rates conditional on applying, but women are less likely to submit applications for junior permanent positions. This finding motivates the next section, where I investigate one possible mechanism behind these application differences: geographic mobility.

3 Data

I built a novel dataset that links all PhD graduates in France to their research output, application behavior, and hiring outcomes in academia. This rich administrative data allows me to track candidates from PhD graduation to permanent junior faculty positions, observing both the universe of job offers and the universe of actual applications. I structure the data at the candidate-job level to analyze how mobility constraints shape application and hiring decisions. This section describes the data sources, variable definitions, and summary statistics. Summary statistics are reported in Table A1.

3.1 Sources

I combine data from three sources: *theses.fr* on PhD graduations, *Scopus* on academic publications, and the *CNU Database* on qualification decisions and job market outcomes. The first two sources were assembled in Bisantis et al. (2026); I describe them briefly here and refer the reader to that paper for details.

I retrieved data from *theses.fr* on all PhD theses defended in French universities from 2000 to 2021. For each PhD thesis, I have information on field of study, defense year, university affiliation, and first and last name of the PhD graduate and the supervisor(s). *Theses.fr* is a centralized, public platform that collects data on all PhD graduations in the French academic system. French universities have the legal obligation to report information on PhD graduations. While some spelling errors and reporting delays are unavoidable, this database is considered as being, overall, comprehensive and reliable.⁷ I focus on PhD theses with one or two supervisors and with non-missing information on field and names.⁸ I exclude theses defended in *Health and Medical Sciences*, because of a misclassification problem specific to this field.⁹

I next assemble information on academic publications of PhD graduates and PhD supervisors. To do so, I extract bibliometric data from *Scopus* on all publications until 2021 where the first name and last name of one author are identical to the first name and last name of a PhD graduate or a PhD supervisor. The risk of mismatch is still significant, however, when the first and last names are very common, such as “Sarah Lopez” or “Philippe Morin”. To address this issue, I remove observations with overly common names, following the procedure described in Bisantis et al. (2026). For each

⁷See <https://theses.fr/> for more information on data collection and on the underlying institutional arrangement.

⁸Theses with three supervisors or more represent less than 2% of the original sample.

⁹To become Medical Doctors, French medical students must defend a *practical thesis* (“Thèse d’exercice”) at the end of their studies. *These practical* theses have very different requirements from PhD theses, but *Theses.fr* did not distinguish between the two until the 2000s.

academic publication, I have information on publication type, journal, year of publication, number of co-authors, and the Article Influence Score (AIS) of the outlet, a classical measure of journal quality (see [Bagues et al. \(2017\)](#)).

I identify the gender of PhD supervisors using well-established methods based on first names. In a first step, I use data from the French statistical institute, *INSEE*, on the numbers of boys and girls born in France between 1940 and 2020 with a given first name. I associate a gender with a first name when at least 95% of individuals with this name share the same gender. In a second step, and to broaden coverage to non-French supervisors, I use similar data from Australia, Canada, Spain, Sweden, the UK, and the US. In the end, I identify the gender of 95% of the supervisors.

Finally, I use data from the Conseil National des Universités (*CNU*), which provides a comprehensive record of qualification decisions, applications and recruitment outcomes for researchers seeking access to junior permanent positions in French universities. For each candidate, I have information on name, gender, birth date, discipline, and a unique candidate number. Using this candidate number, I track all applications to junior permanent positions and observe the selected candidate for each posted job. Note that the CNU discipline classification differs from the field classification used in *theses.fr*; I describe the correspondence between the two in [Table B10](#). I focus on qualified candidates who completed their PhD in a French university, as identified in *theses.fr*. Candidates from outside this sample - typically researchers who obtained their PhD abroad - represent approximately 40% of all qualification applicants and are excluded from the main analysis.

3.2 Candidate-Job Dyad Construction

This study relies on a dyadic dataset that links each PhD graduate qualified to the universe of job openings for junior permanent positions in the French academic market in their discipline across universities and years. The unit of observation is a dyad between a candidate and a job opening within the same academic discipline. To avoid selection bias, I restrict attention to the first year of qualification.

Dyads are constructed by matching each PhD graduate to all job openings posted in their discipline during the relevant year. This approach reflects the actual opportunity set faced by candidates, as application rules and disciplinary boundaries limit cross-discipline mobility. Each dyad is associated with characteristics of the candidate, the job opening, and the hiring university - including geographical distance between the PhD university and the job-posting university.

From this dyadic dataset, I construct an individual-level panel by aggregating across dyads. I exclude job postings in overseas territories (DOM-TOM) except Corsica and

drop graduates or applications associated with those regions (representing 3% of the sample).

The final sample comprises approximately 2,287,593 dyads, constructed from 43,966 qualified PhD graduates and 18,787 job offers across 58 disciplines, spanning the period from 2009 to 2021.

3.3 Main Variables

Outcomes For each dyad, I observe two main outcomes: *Apply* takes the value 1 if the candidate applied for the position, and 0 otherwise. This outcome is used to analyze revealed preferences over job openings. *Success* takes the value 1 if the candidate was selected for the position, and 0 otherwise. This variable captures hiring outcomes.

Controls The vector of controls is composed of age at the year of application and its square; whether individual i has at least one scientific publication appearing in the *Scopus platform* (dummy $Publish_{it}$); the cumulative number of publications at year t ($Quantity_{it}$) and the cumulative Article Influence Score (AIS) of publications at year t ($Quality_{it}$), and supervisor characteristics including whether at least one supervisor is female ($Female_supervisor$) and the cumulative AIS score of supervisors at the year of PhD defense of individual i ($Quality_supervisor_i$). All controls are listed in Table A1.

Distance The main geographic variable is the great-circle (orthodromic) distance between the city of the PhD-granting university and the city of the hiring university, measured in kilometers. I compute this distance “à vol d’oiseau” using geo-coordinates (latitude and longitude), following the Vincenty ellipsoid formula. This measure reflects true geographic separation, abstracting from travel infrastructure. To account for spatial variation in large urban areas and to improve precision in cases where both universities are located in the same city, I follow the approach of Mayer and Zignago (2011) by incorporating the radius of the city. The city radius provides an estimate of the geographical size of each urban area and helps differentiate between genuinely proximate universities and those that may be several kilometers apart within the same city.¹⁰ The use of distance from the PhD university as a measure of spatial frictions is motivated by the concept of *home bias* - the well-documented tendency for individuals to remain near

¹⁰I use INSEE data to obtain the official surface area of each city and compute the radius assuming circular symmetry. Geo-coordinates (longitude and latitude) for each city are also retrieved from INSEE. I compute great-circle distances between cities using the *GEODIST* function in Stata based on these coordinates.

familiar or previously inhabited locations¹¹. While I do not observe candidates’ place of birth, the PhD university serves as a reasonable proxy for “home” for several reasons: (1) Many candidates complete both their Master’s and PhD at the same university,¹²; (2) The PhD period often coincides with long-term personal and professional settlement; (3) Application patterns in the data show strong spatial concentration around the PhD university - for instance, one quarter of applications are submitted within the same region. This interpretation is consistent with recent literature documenting geographic immobility and local labor market attachment: prior residence and university affiliation are shown to influence job search behavior (Kleven et al., 2020; Diamond, 2016).

3.4 Descriptive Statistics

3.4.1 Candidates

Table A1 presents descriptive statistics for the sample of qualified candidates, disaggregated by gender. Women represent 44% of the sample, are slightly older than men on average (34 vs. 33 years), and have spent a similar amount of time since completing their PhD (3 years).

Male candidates are more likely to have at least one publication (64% vs. 49%), publish more (5 vs. 3), and have higher cumulative journal impact scores (AIS: 6 vs. 3). These differences are consistent with the literature on gender gaps in research productivity¹³. Both groups apply to a similar number of positions (3.5 applications), and the probability of securing a position is identical across genders at 9%.

Some of these differences likely reflect disciplinary composition rather than gender per se. Women are more represented in Humanities (31% vs. 18%) and Literature (12% vs. 5%), while men dominate Engineering (13% vs. 6%), Physical Sciences (15% vs. 7%), Mathematics (8% vs. 3%), and Computer Science (11% vs. 4%).

Field-level statistics (Tables B6-B9) show that gender gaps in research productivity and application behavior persist within-but vary across-fields. In STEM, men publish more and apply slightly more; in Humanities, women apply more but publish slightly less. In Biological and Social Sciences, gender differences are minimal. Age also varies considerably across fields: candidates in Humanities and Social Sciences are older on average than those in STEM or Biological Sciences, which likely contributes to the small

¹¹The concept of *home bias* originates in international finance, where it describes the preference for domestic over foreign assets. It is now commonly used in labor and migration contexts to capture individuals’ tendency to remain near familiar or previously inhabited locations.

¹²In France, Master’s programs include research-oriented tracks that often serve as a direct pipeline to a PhD at the same university.

¹³(Holman et al., 2018; Xie and Shauman, 2003; Larivière et al., 2013; Bisantis et al., 2026)

overall gender difference in age, given women’s greater representation in those older fields.

While the magnitude and direction of gender gaps are not uniform across fields, men tend to have higher research output on average, particularly in fields with greater overall publication intensity. These patterns indicate that differences in field composition alone are insufficient to explain all observed gender disparities, reinforcing the importance of including discipline fixed effects in the empirical analysis.

Successful Candidates. Table B5 presents descriptive statistics for candidates who secured a permanent position. Women account for 42% of this group. Among successful applicants, men continue to show higher research output, with more publications (4 vs. 2) and higher cumulative AIS scores (3.25 vs. 1.59). To secure the position, women applied to slightly more positions on average (12 vs. 11) and are, on average, marginally older (33 vs. 32 years). Gender differences in field representation persist: women remain more concentrated in Humanities, Literature, and Management, while men are more represented in Engineering, Computer Science, and Physical Sciences.

Location Figure A1 displays the cumulative number of qualified candidates from 2009 to 2021 by *department*¹⁴, based on the location of their PhD university. The spatial distribution is highly unequal across France. A small number of departments concentrate the majority of qualified candidates. Paris alone accounts for over 14,500 qualified candidates, representing nearly 30% of the national total. Other prominent academic hubs include Rhône (Lyon, 2,612), Haute-Garonne (Toulouse, 2,479), Isère (Grenoble, 1,897), Bouches-du-Rhône (Marseille, 1,995), and Hérault (Montpellier, 1,655). In contrast, more than 40 departments recorded fewer than 100 qualifiers, and over 30 produced none at all during the entire period. I will therefore conduct robustness checks by re-estimating my main specifications on a sample that excludes Paris.

Figure A2 shows the evolution of the number of qualified candidates per department between 2009 and 2021. The left y-axis plots the annual counts for each department (excluding Paris), while the right y-axis displays the national totals. Two versions of the total are shown: a solid line represents the sum excluding Paris, and a dashed line includes Paris. This distinction is necessary because Paris is a strong outlier and would otherwise obscure variation across other departments. The Figure highlights a clear national decline in the number of qualified candidates starting around 2014. Most departments follow a downward trajectory, though the decline is numerically driven by the largest academic centers-particularly Paris and other major university cities.

¹⁴Departments (départements) are French administrative divisions, akin to counties, and serve as a geographic unit in the analysis.

3.4.2 Job Offer

Location. Figure A3 shows the cumulative number of permanent academic job openings by *department* between 2009 and 2021, based on the location of the hiring university. The spatial distribution broadly overlaps with the training locations of qualified candidates, but job openings are overall less concentrated. The department of Paris again dominates with over 4,500 positions, followed by Rhône (1,058), Haute-Garonne (892), Bouches-du-Rhône (749), and Isère (647). However, many other departments offer relatively few jobs: over 30 departments recorded fewer than 100 positions during the entire period, and more than 20 had none at all.

Figure A4 displays the annual number of permanent academic job offers by department between 2009 and 2021. Department-level trends are plotted on the left y-axis, excluding Paris for readability. The right y-axis shows two national totals: the solid line excludes Paris, while the dashed line includes it. As in the case of qualified candidates, the number of job openings has declined significantly since 2014. However, the contraction in job supply is even more pronounced, with a steeper and more sustained decline. This reflects broader university constraints on recruitment and shrinking opportunities.

Figure B8 and Figure B7 document the evolution of both supply and demand in the French academic job market from 2009 to 2021. The number of available junior positions has declined steadily since 2012, across nearly all disciplines. This contraction has been met with relatively stable or increasing numbers of qualified candidates, suggesting a tightening of the market over time. Disciplines such as Humanities consistently offer the largest number of positions, but they also encompass a broader range of discipline (see Table B10 in the Appendix).

4 Gender gap in application behavior

4.1 Results: Dyad Approach to Application Behavior

To estimate how spatial frictions shape job search behavior, I examine the probability that a qualified PhD graduate applies to a given junior permanent position. The unit of observation is a dyad between candidate i and job opening j in discipline d during year t . The sample is restricted to the initial year of job market entry and to job openings within the candidate's discipline of qualification. I estimate the following linear probability model:

$$Y_{ijt}d = \beta_1 \ln(\text{Distance}_{ij}) + \beta_2 \text{Female}_i + \beta_3 \ln(\text{Distance}_{ij}) \times \text{Female}_i + X'_{ijt}d \gamma + FE + \varepsilon_{ijt}d \quad (1)$$

The dependent variable is a binary indicator equal to one if candidate i applied to position j . The key independent variable is the log of the great-circle distance (in kilometers) between the PhD university and the hiring university. I interact $\ln(\text{distance})_{ij}$ with a gender dummy to test whether female candidates are more sensitive to spatial frictions. The vector $X_{ijt}d$ includes controls for candidate age, publication record, and supervisor characteristics. Fixed effects FE varies across specifications.

Table 1: Determinants of Application Behavior: Candidate-Job Dyads

	(1)	(2)	(3)
Dependent variable:	<i>Apply to position</i>		
Female	0.00711** (0.00280)	0.000635 (0.00324)	- -
ln(Distance)	-0.0127*** (0.000319)	- -	-0.0127*** (0.000304)
ln(Distance) \times Female	-0.00238*** (0.000440)	-0.00116** (0.000534)	-0.00235*** (0.000398)
Adj R^2	0.19	0.19	0.30
Controls	yes	yes	yes
Fixed effects	$U_i \times t \times d + U_j \times t \times d$	$U_i \times U_j \times t \times d$	$i \times (t \times d) + j \times (t \times d)$
Observations	2,287,422	2,162,136	2,286,953

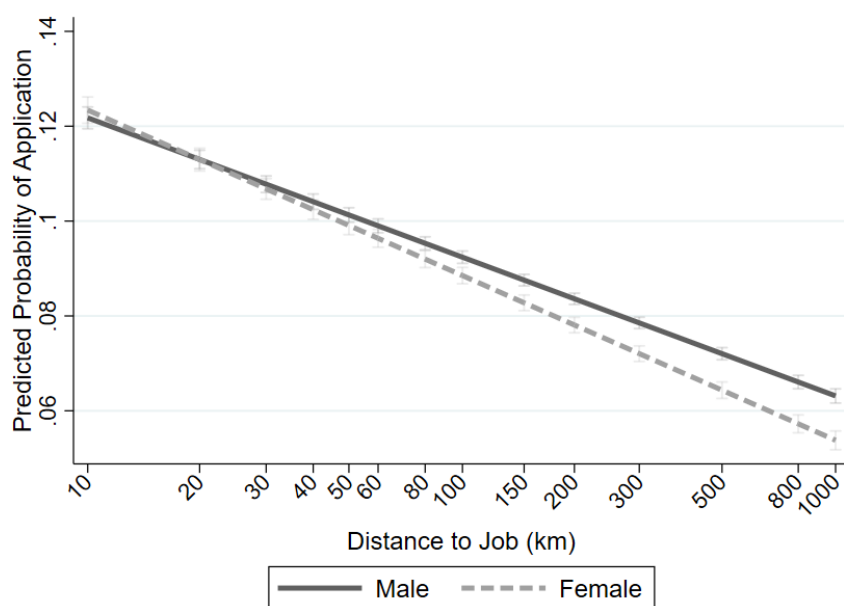
Notes: *Apply* is a binary variable equal to 1 if the candidate applied to a specific job. Each observation represents a dyad between a candidate and a potential job opening. $\ln(\text{Distance})$ is the logarithm of the geographical distance between the job and the candidate's PhD university. All regressions include controls for age, publication metrics, and a dummy equal to 1 if at least one PhD supervisor is female. Fixed effects vary across specifications and are indicated in the "Fixed effects" row: U_i denotes the university of candidate i , U_j the university of the job j , t the year, and d the discipline. i and j denote candidate and job identifiers, respectively. Standard errors are clustered at the discipline \times PhD University \times Year level. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1 presents the estimation results. Across all specifications, the interaction between distance and gender is negative and statistically significant, indicating that female candidates are more geographically affected in their application behavior.

In Column (1), the specification includes university-year-discipline fixed effects for both the candidate's PhD university ($U_i \times t \times d$) and the job university ($U_j \times t \times d$). This specification compares candidates from the same university and discipline applying in the same year, and jobs posted by the same hiring university and discipline in the same year. The coefficient on $\ln(\text{Distance}_{ij})$ therefore captures how variation in distance across dyads - holding constant university characteristics - predicts application decisions.

The coefficient on $\ln(\text{Distance}_{ij})$ is -0.0127 , implying that a 10% increase in distance reduces the probability of application by about 0.13 pp. The interaction term is negative and significant (-0.00238), suggesting that this spatial sensitivity is amplified for women. The combined effect of distance for female candidates is -0.0151 , nearly 20% larger in magnitude compared to men. Figure 2 illustrates this result: the probability of applying declines with distance for both genders, but the slope is notably steeper for women. In Appendix Figures A5 and A6, I show quadratic binscatters that flexibly depict the same pattern. These reveal that women are particularly less likely to apply beyond 200km, and the gap persists across specifications with richer fixed effects.

Figure 2: Predicted Number of Applications by Distance to Job Offers by Gender



Notes: Predicted probability of applying to a job as a function of distance from the candidate’s PhD university, shown separately by gender. Estimates are based on the regression model in column (1) of Table 1 and control for age, publication metrics, supervisor characteristics, and fixed effects. Distance (x-axis) is plotted on the original kilometer scale for interpretability. Standard errors are clustered at the discipline \times PhD University \times Year level.

Column (2) introduces dyadic fixed effects at the PhD university-job university-year-discipline level $U_i \times U_j \times t \times d$. This specification compares candidates from the same PhD university applying to jobs at the same hiring university, within the same discipline and year. The main effect of distance is absorbed, but the interaction term remains negative and statistically significant (-0.00116), confirming that gendered distance effects persist even within narrowly defined university pairs.

Column (3) includes individual-level fixed effects for both candidates and jobs, interacted with year and field ($i \times (t \times d) + j \times (t \times d)$). This approach compares which jobs a given candidate applies to, and which candidates apply to a given job, within

the same discipline and year. By absorbing all individual and job-level characteristics - both observed and unobserved - that are constant within the year-discipline cell, this specification sharpens identification by leveraging only within-candidate variation in job opportunities. The remaining variation in distance captures differential application patterns across jobs faced by the same candidate. The distance coefficient remains negative and highly significant (-0.0127), and the interaction term remains robust (-0.00235). Even when comparing the same candidate across alternative jobs, and the same job across alternative candidates, women remain less likely to apply to geographically distant positions.

4.2 Robustness: Dyad Approach to Application Behavior

The results are robust to a range of alternative specifications. First, Table D11 replaces the logarithmic transformation of distance with the level measure (in kilometers). The interaction between gender and distance remains negative and significant across specifications, confirming that the log-linear form is not driving the result.

Second, I construct a new measure of geographic frictions based on estimated commuting time between the PhD and job location. This variable combines train travel time (from official SNCF timetables), road travel time (based on routing algorithms), and AI-based predictions for less connected pairs. Details of the construction are provided in Appendix Section C.1. As shown in Table D12, the interaction between gender and commuting time remains negative and significant.

Third, I include controls for age at PhD and time since graduation to account for potential differences in life-cycle stage (Table D13). The estimates are unchanged, suggesting that career timing is not a confounding factor.

Fourth, to assess whether the effect is driven by spatial clustering in the Paris region - where job opportunities are dense - Table D14 excludes candidates located in Paris. The gender-distance interaction remains robust, indicating that local agglomeration is not driving the main result.

Fifth, I account for potential selection based on the decision to apply at all. Table D15 presents estimates for several restricted subsamples. Panel A focuses on candidates who applied to at least one job during their entire career, while Panel B restricts further to those who submitted at least one application in their first year of eligibility.

4.3 Heterogeneity in Dyad-Level Results

To better understand the mechanisms underlying this gendered spatial preference, I next examine how the distance penalty varies across key dimensions of candidate heterogeneity.

Table [D17](#) explores heterogeneity in the gender-distance interaction by candidate age, time since PhD, academic productivity.

Age and Career Stage. Panels A and B split the sample by the median candidate age at application and years since PhD, respectively. The gender-distance interaction is negative and statistically significant in both younger and older groups, but the magnitude is larger among older candidates and those who are further from graduation. For example, among those with above-median time since PhD, the interaction term is -0.00288 compared to -0.00150 for newer graduates

Research Productivity Panels C and D examine heterogeneity by candidates' academic productivity, measured by AIS (Article Influence Score) and number of publications. The gender-distance gap is significant regardless of research output, but larger among those without any publications. For instance, women with no publications face a higher distance penalty (-0.00207) than their male peers, while those with publications still show a significant, but smaller, gap.

After First Year of Qualification. Panels C to E of Table [D15](#) examine how the gender-distance interaction evolves over time by estimating the model separately for candidates still on the job market in their second, third, and fourth years after PhD qualification. While the main analysis focuses on first-year applicants to avoid selection bias from lower-performing candidates who remain on the market longer, this extended analysis allows me to assess whether gendered spatial frictions persist beyond initial market entry. Across all subsequent years, the gender-distance interaction remains negative and statistically significant, though its magnitude gradually declines. This suggests that spatial preferences are most binding for women at the start of their academic careers, but continue to shape application behavior even in later years.

Heterogeneity by Fields Finally, Table [D16](#) explores whether the gender-distance interaction varies across broad disciplinary categories. The interaction is negative and statistically significant in STEM (Panel C) and Social Sciences (Panel D), where job markets are more dispersed and geographic mobility expectations higher. In contrast, the coefficients are smaller and not statistically significant in Biology and Humanities (Panels A and B), possibly due to tighter geographic clustering of job postings and smaller sample sizes. These differences point to important field-specific variation in how spatial preferences manifest across the academic labor market.

4.4 Results: Individual-level Application Behavior

To complement the dyadic analysis, I examine gender differences in the number of applications submitted, distinguishing between nearby (within 100 km) and distant (over 100 km) job opportunities. The goal is to test whether the responsiveness to local versus distant job market conditions varies by gender. I estimate Equation (2), where the outcome is the log number of applications (plus one) submitted by each candidate to jobs in either distance *type*:

$$Y_{it}^{type} = \beta_1 Female_i + \beta_2 Offers_{tf}^{type} + \beta_3 Female_i \times Offers_{tf}^{type} + X_i' \gamma + \delta_{tf} + \mu_{u(i)f} + \varepsilon_{it} \quad (2)$$

where Y_{it} denotes the number of applications that candidate i submits in year t to jobs of type *type* (either nearby or distant). The term $Offers_{tf}^{type}$ captures the number of job openings available in field f and year t for each category of distance (either under 100km or over 100km). The interaction term tests whether the responsiveness to job market thickness differs by gender. The vector X_i includes candidate-level controls for age, publication record, supervisor productivity, and a dummy equal to 1 if at least one PhD supervisor is female. The model includes fixed effects for field-year (δ_{tf}) and for PhD university-field ($\mu_{u(i)f}$), thereby accounting for both time-varying field-specific shocks and university heterogeneity in PhD university.

Table 2: Gender Differences in Application Patterns by Distance to Job Offers

Dependent variable:	Applications to Nearby Jobs ($\leq 100km$)			Applications to Distant Jobs ($>100km$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(near\ apps + 1)$	$\ln(near\ apps + 1)$	$\ln(near\ apps + 1)$	$\ln(far\ apps + 1)$	$\ln(far\ apps + 1)$	$\ln(far\ apps + 1)$
Female	-0.0212*** (0.00403)	-0.0231*** (0.00404)	-0.00912** (0.00413)	-0.0267*** (0.00870)	-0.0334*** (0.00870)	-0.0319*** (0.00900)
Near offers	0.0280*** (0.000789)	0.0281*** (0.000791)	0.0300*** (0.00124)			
Female \times Near offers	0.00453*** (0.000968)	0.00460*** (0.000966)	0.00132 (0.00101)			
Far offers				0.0172*** (0.000736)	0.0170*** (0.000733)	0.0106*** (0.00155)
Female \times Far offers				-0.000145 (0.000352)	-0.000137 (0.000350)	-0.000276 (0.000358)
Adj R^2	0.33	0.33	0.38	0.32	0.33	0.35
Controls		yes	yes		yes	yes
Fields X Year FE	yes	yes	yes	yes	yes	yes
Fields X Univ PhD FE			yes			yes
Observations	68258	68258	67617	68258	68258	67617

Notes: The dependent variable is the natural logarithm of the number of applications plus one, submitted by candidates, separately for nearby job offers (within 100km) and distant job offers (over 100km). Control variables include age, publication metrics, a dummy equal to 1 if at least one PhD supervisor is female, and supervisor productivity. Standard errors are clustered at the field \times PhD University \times Year level. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 reports the results. Columns (1)-(3) focus on applications to nearby jobs. Across all specifications, women submit fewer local applications than men: the female coefficient is negative and statistically significant, ranging from -0.021 to -0.009 . This implies that, conditional on observables, women submit about 1-2% fewer local applications on average. However, the gap becomes smaller and loses significance in column (3), which includes PhD university fixed effects, suggesting that university sorting partly explains the difference.

Importantly, the interaction term between Female and Near Offers is positive and significant in columns (1) and (2), indicating that women are more responsive to increases in the number of local job openings. In other words, women apply less overall, but are more elastic to local market conditions. From columns (4) and (6), the gender gap is more pronounced and robust: women submit significantly fewer distant applications across all specifications (around -0.03), and the Female \times Far Offers interaction is small and statistically insignificant. This suggests that female candidates are less responsive to increases in distant job availability, consistent with a stronger preference against mobility.

Overall, these individual-level results reinforce the findings from the dyadic analysis. Female candidates apply to fewer jobs overall, and this gap is especially salient for distant positions. Moreover, women exhibit greater responsiveness to variation in nearby job openings but not to distant ones. These patterns support the interpretation that spatial frictions are more binding for female candidates, leading to differential application behavior even after controlling for research productivity, supervisor quality, and field-level opportunity structures.

4.5 Robustness Checks: Individual-level Results

Table D18 re-estimates the Table 1 using Poisson Pseudo-Maximum Likelihood (PPML) rather than log-linear models. The estimates remain stable in magnitude and direction, confirming that the findings are not driven by functional form assumptions.

In Tables D20-D23 I implement the same robustness checks symmetric to those shown in Table D11 to D16. Results remain consistent throughout and are in line with the patterns observed of the dyadic approach.

Table D23 examines heterogeneity across fields. While the interaction between gender and geographic distance is consistently negative and significant in the pooled regressions, the coefficients are not statistically significant within individual fields. This likely reflects a combination of reduced statistical power and potential heterogeneity across fields. Importantly, the point estimates are generally in the same direction across fields, suggesting that the absence of significance may not reflect an absence of effect.

Finally, Table D24 uses alternative measures of geographic proximity, redefining “local” markets at the city and region level, respectively. The interaction between gender and local job density remains positive and significant in both cases, further supporting the interpretation that women are more sensitive to distance in their application behavior.

Taken together, these results provide robust evidence that spatial distance significantly discourages job applications, and that this deterrent effect is stronger for women. Gendered spatial preferences in the job search process persist even after conditioning on academic productivity, career stage, supervisor characteristics, and fixed effects at the PhD, job, university, and field level.

5 From Applications to Securing a Junior Permanent Position

The previous section documented significant gender differences in application behavior, especially in response to geographic distance. But applying is only the first step in the academic job market. This section investigates how application behavior translates into hiring outcomes: are men and women equally likely to secure a position, conditional on how many jobs they apply to? And to what extent does the spatial structure of the job market shape these outcomes?

5.1 Geographic Market Structure: Average Distance of Job Offers

Job Offer Average Distance Index. To capture spatial constraints in the academic job market, I construct a measure of the Average Distance between a candidate’s PhD university and the universe of job openings available in their discipline and year of application. Formally, the average distance for candidate i in discipline d and year t is defined as:

$$\text{Av. Distance}_{ijdt} = \frac{\sum_j \text{Distance}_{ij}}{\sum_j N_{dt}}, \quad (3)$$

where Distance_{ij} is the great-circle distance between candidate i ’s PhD university and each job posting j in their discipline and year, and N_{dt} is the total number of such positions. A higher value means that jobs this year are more distant from the university of PhD graduation.

The Average Distance variable is defined at the discipline-year level and captures variation in the geographic structure of the job market that is plausibly exogenous to

individual candidates' preferences, qualifications, or strategies. In the French academic system, job openings are announced centrally and only after candidates complete their PhD and obtain the national qualification. As a result, candidates cannot anticipate the geographic configuration of the market they face in their year of entry.

This structure introduces idiosyncratic, quasi-random variation across cohorts and discipline in how geographically distant the available jobs are. These exogenous differences affect all candidates within a discipline-year but may have differential consequences across subgroups, such as men and women. In particular, if some candidates are more sensitive to geographic constraints than others, variation in average distance can translate into differences in the number of applications submitted and, ultimately, in hiring success.

Because this variation operates at the individual level, it allows for a credible analysis of how job market geography affects application behavior and the probability of securing a position.

5.2 Estimation Model

To investigate how application behavior relates to hiring outcomes, I estimate a series of OLS regressions at the candidate level. The dependent variable varies across specifications: it is either a binary indicator equal to 1 if a candidate secures a junior permanent academic position (*Success*), a binary indicator equal to 1 if the candidate submits at least one application (*Apply dummy*), or the log number of applications submitted ($\ln(Apps)$).

The main explanatory variables are the number of applications submitted, measured as $\ln(Apps)$, and the *Average Distance*, defined as the average great-circle distance between a candidate's PhD university and all job openings in their discipline and year of first qualification. To explore gender differences, I include a dummy variable for females and interact it with each of these key regressors. This allows both the effect of applying and the sensitivity to market geography to vary by gender. A central feature of the analysis is the distinction between two margins of application behavior. The *extensive margin* captures whether a candidate enters the market at all, while the *intensive margin* captures how many applications are submitted conditional on applying. To separate these two channels, I estimate the effect of *Average Distance* both on the full sample and on the restricted subsample of candidates who submitted at least one application. Comparing estimates across these two samples allows me to assess whether geographic distance operates primarily by discouraging market entry or by reducing search intensity among active applicants.

Model 1: Applications and Hiring

$$\text{Success}_i = \beta_0 + \beta_1 \ln(\text{Apps}_i + 1) + \beta_2 \text{Female}_i + \beta_3 \text{Female}_i \times \ln(\text{Apps}_i + 1) + X_i' \gamma + \delta_{ft} + \delta_{uf} + \varepsilon_i \quad (4)$$

This regression estimates the relationship between the number of applications and the probability of securing a job. It also tests whether this relationship differs for men and women.

Model 2: Distance and Application Behavior

$$\text{Apply dummy}_i = \alpha_0 + \alpha_1 \text{AvgDistance}_{ft} + \alpha_2 \text{Female}_i \times \text{AvgDistance}_{ft} + X_i' \lambda + \delta_{ft} + \delta_{uf} + u_i \quad (5)$$

$$\ln(\text{Apps}_i) = \pi_0 + \pi_1 \text{AvgDistance}_{ft} + \pi_2 \text{Female}_i \times \text{AvgDistance}_{ft} + X_i' \mu + \delta_{ft} + \delta_{uf} + v_i \quad (6)$$

Equation 5 estimates how average market distance affects the probability of submitting at least one application, capturing the extensive margin of participation. Equation 6 studies how distance affects the number of applications submitted, estimated both on the full sample and on the subsample of candidates who applied at least once. Comparing these two estimates allows me to determine whether geographic distance operates through market entry or through search intensity conditional on entry. The interaction terms allow for gender-specific responses to market geography in both equations.

Model 3: Distance and Hiring

$$\text{Success}_i = \theta_0 + \theta_1 \text{Av. Distance}_{ft} + \theta_2 \text{Female}_i \times \text{Av. Distance}_{ft} + X_i' \phi + \delta_{ft} + \delta_{uf} + \eta_i \quad (7)$$

Model 7 tests whether the average distance of job opportunities directly affects hiring outcomes. A negative coefficient would suggest that candidates are less likely to be hired when job openings are, on average, farther from their PhD university, either because fewer candidates enter the market or because those who do apply face greater constraints.

In these equations, the vector X_i includes controls for age, research productivity (both quantity and quality), a dummy equal to 1 if at least one PhD supervisor is female, and PhD supervisor research quality. All regressions include fixed effects for field-year (δ_{ft}) and field-PhD university (δ_{uf}), which capture variation in job market conditions and university training quality. Standard errors are clustered at the field \times PhD university \times year level.

5.3 Empirical Results: Applications, Distance, and Hiring

This section presents the empirical results from the models described above. I begin by estimating how application intensity relates to hiring outcomes, then assess how average market distance affects both the decision to apply and the number of applications submitted, and finally examine whether these effects differ by gender.

Table 3: Application Behavior and Hiring Outcomes: OLS and Reduced-Form Estimates

Dependent variable:	(1) Success	(2) Apply dummy	(3) ln(Apps)	(4) ln(Apps+1)	(5) Success	(6) Success
Female	-0.00489 (0.00318)	-0.0182*** (0.00448)	-0.00215 (0.0310)	0.0348 (0.0287)	0.0121 (0.0171)	0.0116 (0.00895)
ln(Apps+1)	0.0855*** (0.00167)					
Female \times ln(Apps+1)	0.00346 (0.00230)					
Av. Distance			0.0000420 (0.000113)	-0.000346*** (0.0000874)	-0.000241*** (0.0000623)	-0.0000986*** (0.0000273)
Female \times Av. Distance			-0.0000759 (0.0000833)	-0.000211*** (0.0000752)	-0.0000512 (0.0000458)	-0.0000470** (0.0000235)
Controls	yes	yes	yes	yes	yes	yes
$f \times U_i + f \times t$ FE	yes	yes	yes	yes	yes	yes
Sample	Full	Full	Apps > 0	Full	Apps > 0	Full
Observations	51,391	51,391	26,635	51,391	26,635	51,391

Notes: All regressions are estimated by OLS. The dependent variable is *Success*, a binary indicator equal to 1 if the candidate secures a junior permanent academic position, in columns (1), (5), and (6); *Apply dummy*, a binary indicator equal to 1 if the candidate submits at least one application, in column (2); *ln(Apps)*, the log number of applications submitted, in columns (3) and (4). The key explanatory variables are: *ln(Apps)*, the log number of applications submitted by the candidate; *Female*, a dummy equal to 1 for women; *Average Distance*, defined as the mean great-circle distance between the candidate's PhD university and all job openings in their discipline and year of first qualification; and their interactions with *Female*. Columns (3) and (5) are estimated on the subsample of candidates who submitted at least one application ($Apps > 0$), while columns (2), (4), and (6) use the full sample. All specifications include controls for age, research productivity (quantity and quality), a dummy equal to 1 if at least one PhD supervisor is female, and PhD supervisor research quality, as well as fixed effects for field-year and field-university. Standard errors are clustered at the field \times PhD University \times Year level and reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 presents OLS estimates across six specifications. The dependent variables vary across columns: *Success* in columns (1), (5), and (6), a binary indicator for whether the candidate submits at least one application (*Apply dummy*) in column (2), *ln(Apps)* among applicants in column (3), and *ln(1 + Apps)* in the full sample in column (4). In column (1), application intensity is also measured using *ln(1 + Apps)* because the specification uses the full sample. All specifications include controls for candidate characteristics, field-year fixed effects, and field-university fixed effects with standard errors clustered at the field \times PhD University \times Year level

Column (1) estimates the relationship between application intensity and the probability of being hired. The coefficient on *ln(1 + Apps)* is 0.0855 and statistically significant at the 1% level. This implies that a 10% increase in $1 + Apps$ is associated with an

approximately 0.86 pp increase in the probability of securing a permanent position. For candidates with a positive number of applications, this can be interpreted approximately as the link between a 10% increase in applications and hiring success.

The interaction term, $\text{Female} \times \ln(1 + \text{Apps})$, is positive but statistically insignificant, suggesting that the estimated relationship between application intensity and hiring success is similar for men and women.

Column (2) examines gender differences in market participation, using *Apply dummy* as the dependent variable. The coefficient on *Female* is negative and statistically significant, at -0.0182 , indicating that women are 1.8 pp less likely to submit at least one application.

Columns (3) and (4) then examine the relationship between geographic distance and application intensity. Column (3) restricts the sample to candidates who submitted at least one application and uses $\ln(\text{Apps})$ as the dependent variable, while column (4) uses the full sample and therefore uses $\ln(1 + \text{Apps})$. Among applicants, the coefficient on *Average Distance* is small and statistically indistinguishable from zero, and the interaction with *Female* is also insignificant. By contrast, in the full sample, the coefficient on *Average Distance* is -0.000346 and statistically significant at the 1% level. This implies that a 100 km increase in average distance is associated with an approximately 3.5% decrease in $1 + \text{Apps}$. The interaction with *Female* is also negative and significant. For women, the total effect is -0.000557 , implying that a 100 km increase in average distance is associated with an approximately 5.6 log-point decrease in $1 + \text{Apps}$.

These results suggest that geographic distance affects application behavior mainly through the extensive margin: Distance is associated with lower application activity in the full sample, especially among women, but has little detectable association with application intensity among candidates who submit at least one application.

Columns (5) and (6) estimate the association between geographic distance and hiring outcomes, again separating the sample of applicants from the full sample. In column (5), restricted to candidates who applied, the coefficient on *Average Distance* is -0.000241 and statistically significant at the 1% level. This implies that, among applicants, a 100 km increase in average distance is associated with a 2.41 pp decrease in the probability of securing a position. The interaction with *Female* is negative but not statistically significant.

In column (6), using the full sample, the coefficient on *Average Distance* is -0.0000986 and statistically significant at the 1% level. This implies that a 100 km increase in average distance is associated with a 0.99 pp decrease in the probability of securing a position for male candidates. The interaction with *Female* is -0.0000470 and statistically significant at the 5% level, implying an additional 0.47 pp decrease for women. The total association

for women is therefore approximately 1.46 pp ($(-0.0000986 - 0.0000470) \times 100$) decrease in the probability of securing a position for a 100 km increase in average distance.

5.4 Graphical Evidence: Hiring Outcomes and Market Distance

To complement the regression analysis, I provide a graphical illustration of how geographic distance relates to hiring outcomes, conditional on application.

Figure 3 plots the probability of being hired into a job, given that an application was submitted, against the distance between the candidate’s PhD university and the job location. This conditional approach abstracts from differences in application behavior and focuses on the final stage of the hiring process.

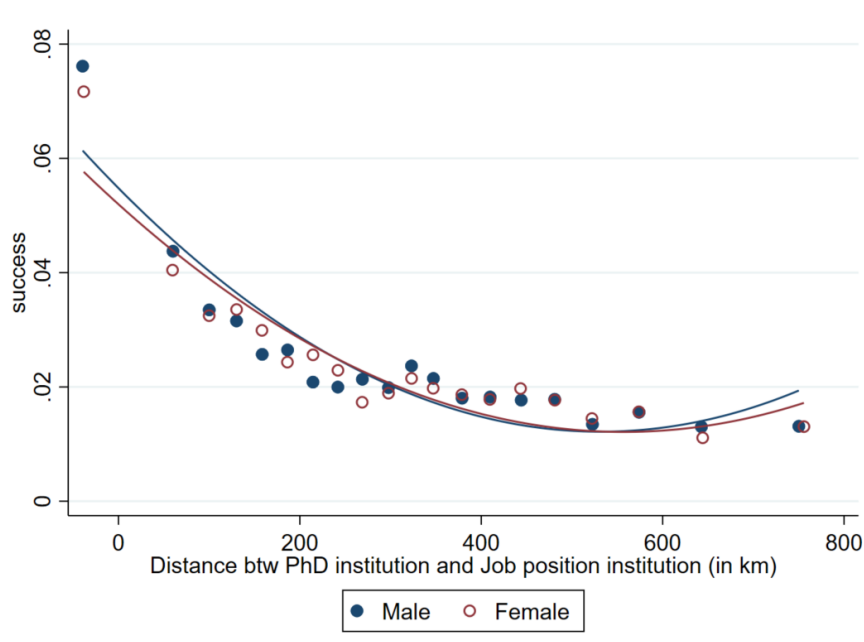


Figure 3: Hiring Probability Conditional on Applying, by Distance and Gender

Notes: The figure shows binned averages of the hiring probability, conditional on application, by distance between the candidate’s PhD university and the job posting (in kilometers). Quadratic fits are plotted separately for men (solid blue circles) and women (red open circles). The regression includes fixed effects for job field-university-year, and controls for age (and age squared), publication quantity and quality, and supervisor characteristics.

This approach follows [Le Barbanchon et al. \(2021\)](#), who analyze hiring patterns conditional on application. The figure in this paper reveals a strong negative relationship between distance and hiring probability for both men and women: success rates fall as jobs are located farther away from the candidate’s PhD university and the two curves track each other closely.

Table [A4](#) confirms this pattern. The probability of being hired declines with distance for both genders. While the marginal effect is slightly smaller for women, the difference

is small and only marginally significant. This suggests that, conditional on applying, women are not penalized more than men based on geographic distance.

5.5 Back-of-the-Envelope Quantification

To quantify how job market geography contributes to gender disparities in hiring, I use a back-of-the-envelope calculation based on the estimates from Model 7. This model relates the average distance between a candidate’s PhD university and available job openings to the probability of securing a permanent academic position.

Let $\hat{\theta}_1$ denote the coefficient on *Average Distance* and $\hat{\theta}_2$ the coefficient on its interaction with the female dummy. The effect of average market distance on hiring outcomes is then computed separately for men and women as:

$$\text{Effect}_{\text{men}} = \hat{\theta}_1 \times \overline{\text{Distance}}$$

$$\text{Effect}_{\text{women}} = (\hat{\theta}_1 + \hat{\theta}_2) \times \overline{\text{Distance}}.$$

Using the estimates from Table 3, Column (6), with $\hat{\theta}_1 = -0.0000986$, $\hat{\theta}_2 = -0.0000470$, and an average market distance for all candidates of 365 kilometers, the implied effects are a 3.6 pp reduction in hiring probability for men and a 5.31 pp reduction for women. The difference, equal to 1.7 pp, captures women’s stronger sensitivity to distance, relative to men, in their likelihood of securing a position, conditional on facing the same job market structure, relative to men. Given a baseline hiring rate of 8.6% in our sample (see Table A), this gap represents approximately 20% of the average success probability.

6 Conclusion

This paper investigates how geographic mobility constraints contribute to gender disparities in academic hiring, using comprehensive administrative data on all PhD graduates and job openings in France between 2009 and 2021. By linking each candidate to the full set of job opportunities in their discipline and year, I construct a novel candidate-position dataset to study how spatial frictions, particularly distance from the PhD university, influence both application decisions and hiring outcomes.

The analysis yields three main findings. First, candidates are less likely to apply to geographically distant positions, and this distance gradient is significantly stronger for women. Second, geographic constraints affect application behavior and hiring outcomes: candidates facing more distant job markets are less likely to enter the market and less

likely to secure a permanent academic position. This effect operates mainly through the extensive margin of applications, as distance has little detectable relationship with the number of applications submitted among candidates who apply at least once. Third, the gender gap does not appear to be driven by stronger employer-side penalties against women conditional on application. Instead, the evidence points to gender differences in application behavior as a key mechanism through which mobility constraints translate into unequal hiring outcomes.

A back-of-the-envelope calculation suggests that women's stronger sensitivity to geographic distance lowers their probability of securing a position by 1.7 percentage points relative to men, when both are evaluated at the same average market distance. This magnitude represents approximately 20% of the average hiring rate in the sample.

An important challenge for future research is to understand the roots of women's lower geographic mobility across labor markets. Potential explanations include family responsibilities, dual-career considerations, and attachment to place, but direct evidence remains limited. Clarifying whether these constraints are primarily structural, cultural, or personal is essential to designing effective policies that promote equal access to job opportunities.

References

- Antecol, Heather, Kelly Bedard, and Jenna Stearns**, “Equal but Inequitable: Who Benefits from Gender-Neutral Tenure Clock Stopping Policies?,” *American Economic Review*, September 2018, *108* (9), 2420–41.
- Bagues, Manuel, Mauro Sylos-Labini, and Natalia Zinovyeva**, “Does the Gender Composition of Scientific Committees Matter?,” *American Economic Review*, April 2017, *107* (4), 1207–38.
- Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet**, “Gender Differences in Job Search: Trading off Commute against Wage*,” *The Quarterly Journal of Economics*, 10 2021, *136* (1), 381–426.
- Bisantis, Aliénor**, “Gender Disparities in French Academic Careers: A Multi-Stage Analysis of Selection,” 2026. Manuscript in preparation. Available upon request.
- , **Yann Bramoullé, and Roberta Ziparo**, “Missing Women in Research,” *WP*, 2026.
- Bosquet, Clément, Pierre-Philippe Combes, and Cecilia García-Peñalosa**, “Gender and promotions: Evidence from academic economists in France,” *The Scandinavian Journal of Economics*, 2019, *121* (3), 1020–1053.
- Card, David, Stefano DellaVigna, Patricia Funk, and Nagore Iriberry**, “Gender differences in peer recognition by economists,” *Econometrica*, 2022, *90* (5), 1937–1971.
- Corsini, Alberto, Michele Pezzoni, and Fabiana Visentin**, “What makes a productive Ph.D. student?,” *Research Policy*, 2022, *51* (10), 104561.
- Diamond, Rebecca**, “The Determinants and Welfare Implications of US Workers’ Diverging Location Choices by Skill: 1980-2000,” *American Economic Review*, March 2016, *106* (3), 479–524.
- Dossi, Gaia**, “Race and Science,” *WP*, 2024, (4).
- Ductor, Lorenzo, Sanjeev Goyal, and Anja Prummer**, “Gender and collaboration,” *Review of Economics and Statistics*, 2023, *105* (6), 1366–1378.
- Dupas, Pascaline, Amy Handlan, Alicia Sasser Modestino, Muriel Niederle, Mateo Seré, Haoyu Sheng, Justin Wolfers, and The Seminar Dynamics Collective**, “Gender differences in economics seminars,” *American Economic Review*, 2026.

- Galván, Estefanía and Victoria Tenenbaum**, “Gender gaps in academia: The role of children,” *Journal of Economic Behavior Organization*, 2026, *241*, 107380.
- Gaule, Patrick and Mario Piacentini**, “An advisor like me? Advisor gender and post-graduate careers in science,” *Research Policy*, 2018, *47* (4), 805–813.
- Ginther, Donna and Shulamit Kahn**, “Women in Economics: Moving Up or Falling Off the Academic Career Ladder?,” *Journal of Economic Perspectives*, 02 2004, *18*, 193–214.
- Hengel, Erin**, “Publishing while female: Are women held to higher standards? Evidence from peer review,” *The Economic Journal*, 2022, *132* (648), 2951–2991.
- Holman, Luke, Devi Stuart-Fox, and Cindy E. Hauser**, “The gender gap in science: How long until women are equally represented?,” *PLoS Biology*, 2018, *16* (4), e2004956.
- J., Williams W. M. Ceci S.**, “Understanding current causes of women’s underrepresentation in science,” *PNAS Proceedings of the National Academy of Sciences of the United States of America*, 2011.
- J., Gates A. J. Sinatra R. Barabási A.-L. Huang**, “Historical Comparison of Gender Inequality in Scientific Careers across Countries and Disciplines.”, *Proceedings of the National Academy of Sciences*, 2020.
- J., Ginther D. K. Kahn S. Williams-W. M. Ceci S.**, “Women in Academic Science: A Changing Landscape,” *Psychological science in the public interest : a journal of the American Psychological Society*, 2014.
- Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaaard**, “Children and Gender Inequality: Evidence from Denmark,” *American Economic Journal: Applied Economics*, October 2019, *11* (4), 181–209.
- , – , **Mathilde Muñoz, and Stefanie Stantcheva**, “Taxation and Migration: Evidence and Policy Implications,” *Journal of Economic Perspectives*, May 2020, *34* (2), 119–42.
- Koffi, Marlène**, “Innovative Ideas and Gender (In)equality,” *American Economic Review*, July 2025, *115* (7), 2207–36.
- Larivière, Vincent, Cassidy R. Sugimoto, Yves Gingras, Blaise Cronin, and Chaoqun Ni**, “Bibliometrics: Global gender disparities in science,” *Nature*, 2013, *504*, 211–213.

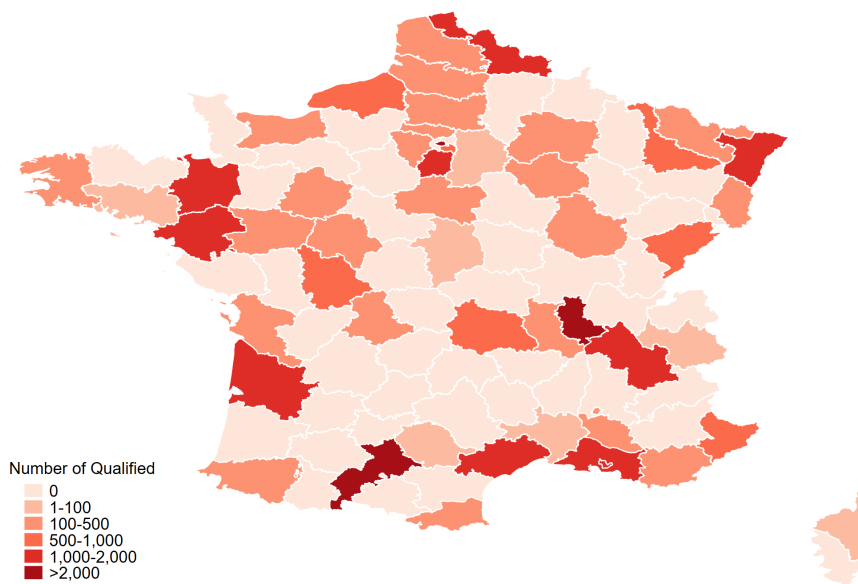
- Lassen, Anne Sophie and Ria Ivandić**, “Parenthood and Academic Career Trajectories,” *AEA Papers and Proceedings*, May 2024, *114*, 238–42.
- Lerchenmueller, Marc J. and Olav Sorenson**, “The gender gap in early career transitions in the life sciences,” *Research Policy*, 2018, *47* (6), 1007–1017.
- Mayer, Thierry and Soledad Zignago**, “Notes on CEPII’s distances measures: The GeoDist database,” Working Papers 2011-25, CEPII research center Dec 2011.
- Meyer, Meredith, Andrei Cimpian, and Sarah-Jane Leslie**, “Women are underrepresented in fields where success is believed to require brilliance,” *Frontiers in Psychology*, 2015, *6*.
- Patsali, Sofia, Michele Pezzoni, and Fabiana Visentin**, “Research independence: drivers and impact on PhD students’ careers,” *Studies in Higher Education*, 02 2024, pp. 1–24.
- Sarsons, Heather**, “Recognition for Group Work: Gender Differences in Academia,” *American Economic Review*, May 2017, *107* (5), 141–145.
- Wu, Alice H.**, “Gendered Language on the Economics Job Market Rumors Forum,” *AEA Papers and Proceedings*, May 2018, *108*, 175–79.
- Xie, Yu and Kimberlee A. Shauman**, “Sex Differences in Research Productivity: New Evidence about an Old Puzzle,” *American Sociological Review*, 2003, *68* (6), 847–870.

Appendix

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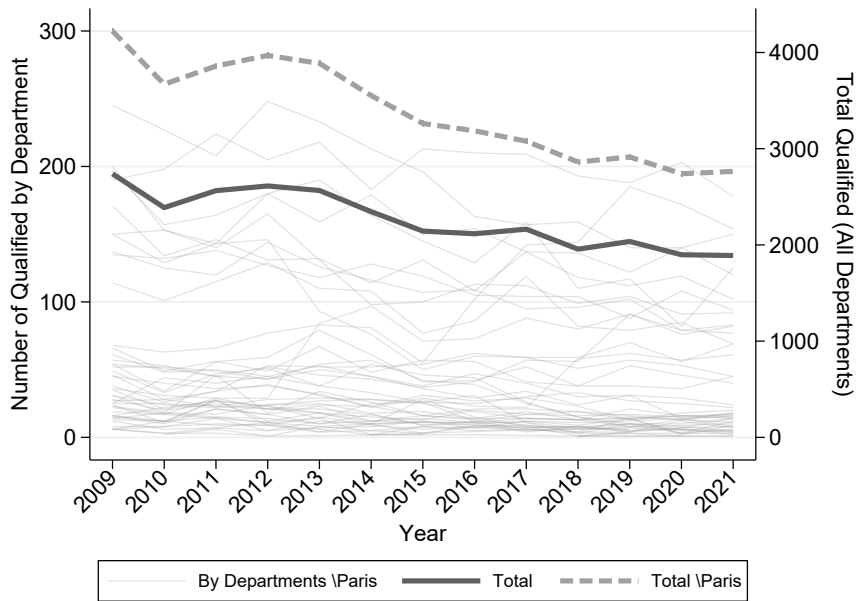
A Additional Figures and Tables

Figure A1: Cumulative Number of Qualified Candidates by Department of PhD (2009–2021)



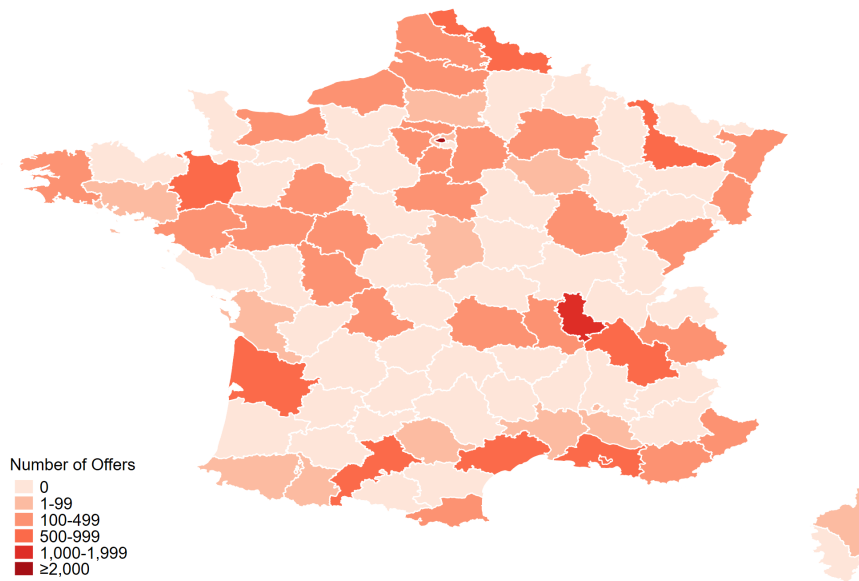
Notes: This map shows the total number of candidates qualified for junior permanent academic positions (*Maître de Conférence*) between 2009 and 2021, based on the city location of their PhD institution. Values are aggregated at the departmental level (96 mainland French departments). Departments with darker shading indicate higher numbers of qualified candidates. The spatial distribution is highly concentrated, with Paris (département 75) alone accounting for over 14,500 qualifiers - nearly 30% of the national total. 30 rural or peripheral departments recorded zero qualifiers over the same period.

Figure A2: Annual Number of Qualified Candidates by Department (2009–2021)



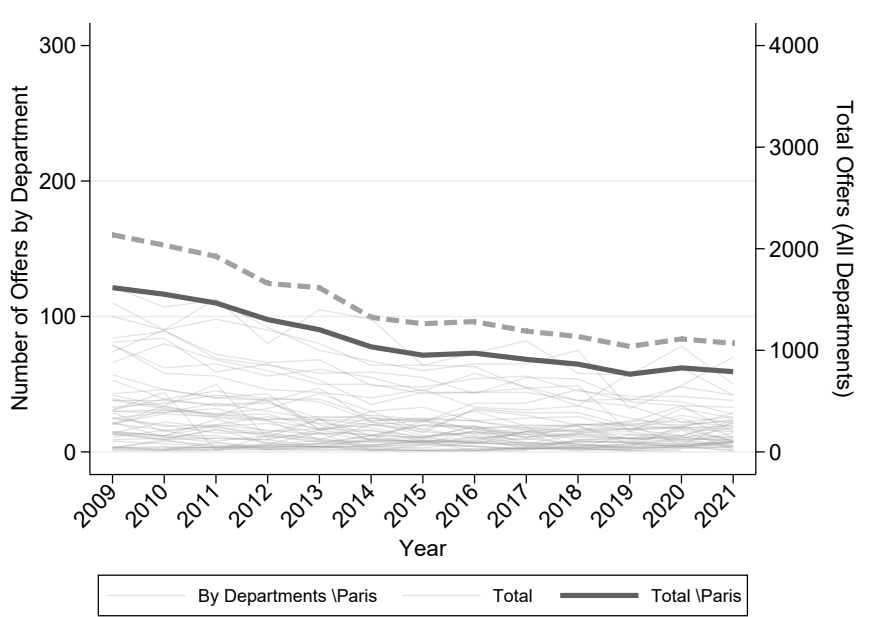
Notes: The figure shows the annual number of candidates qualified to apply for junior permanent academic positions (*Maître de Conférence*) from 2009 to 2021, by *department* of PhD graduation’s city. Department-level trends (left y-axis) exclude Paris to improve readability. Two national totals are shown on the right y-axis: the dashed line includes Paris, while the solid line excludes it. Paris is excluded from the department lines due to its much larger volume (over 14,500 qualifiers during the period), which would otherwise compress variation across other departments.

Figure A3: Cumulative Number of Permanent Academic Job Offers by Department (2009–2021)



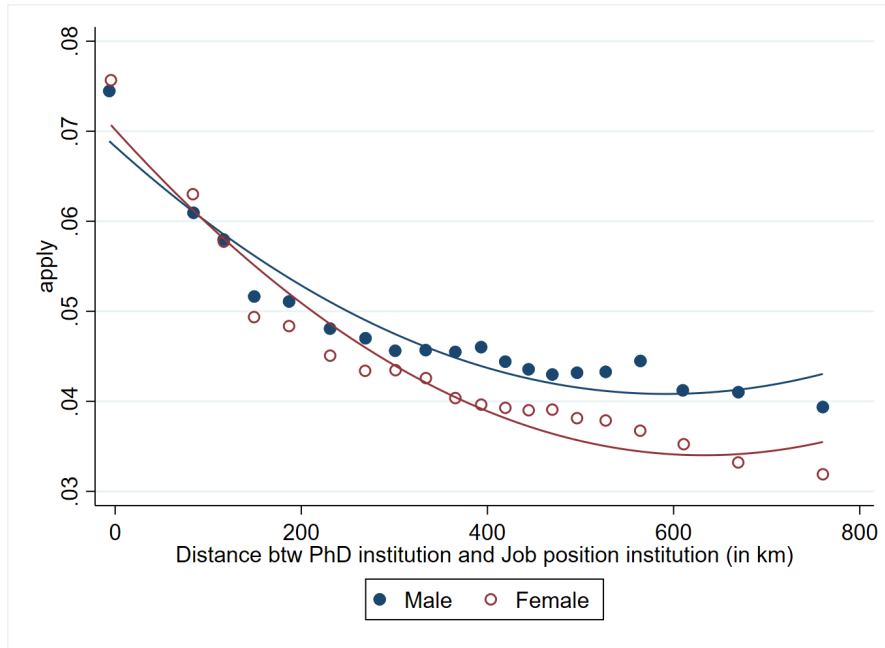
Notes: This map shows the cumulative number of junior permanent academic (*Maître de Conférence*) job offers between 2009 and 2021, aggregated by the *département* of the hiring institution. The color scale is consistent with Figure A1 (qualified candidates), allowing for visual comparison. Paris (*département* 75) had the highest number of positions (4,529), while more than 20 *départements* recorded zero offers during this period.

Figure A4: Annual Number of Permanent Academic Job Offers by Department (2009–2021)



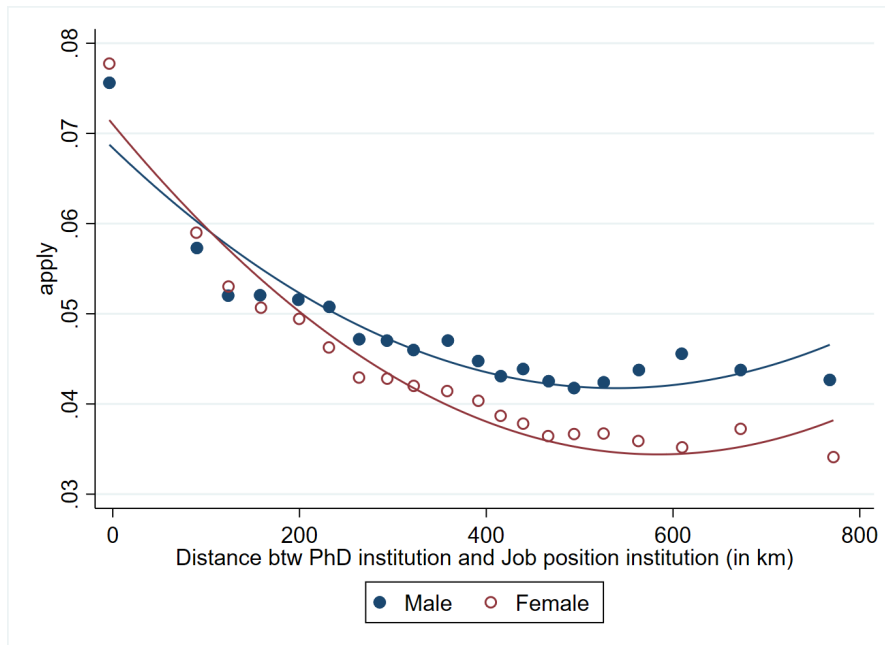
Notes: This figure shows the number of junior permanent academic (*Maître de Conférence*) job offers from 2009 to 2021. Department-level trends are plotted on the left y-axis (excluding Paris for readability). The right y-axis displays national totals: the dashed line includes Paris, while the solid line excludes it. Paris is excluded from department-level lines due to its large scale, which would otherwise compress variation across other departments.

Figure A5: Probability to Apply by Distance to Job Offers by Gender



Notes: The figure presents a binned scatterplot of the application rate versus the distance from the candidate's PhD institution and the position institution, shown separately by gender. The application rate and distance are residualized controlling for age, publication metrics, supervisor characteristics, and PhD institution \times Field \times year fixed effects.

Figure A6: Probability to Apply by Distance to Job Offers by Gender



Notes: The figure presents a binned scatterplot of the application rate versus the distance from the candidate's PhD institution and the position institution, shown separately by gender. The application rate and distance are residualized controlling for age, publication metrics, supervisor characteristics, and Job position's institution \times Field \times year fixed effects.

Table A1: Descriptive Statistics

Variable	<i>Male</i>			<i>Female</i>		
	N	Mean	SD	N	Mean	SD
Apply Position	28,822	0.51	0.50	22,722	0.53	0.50
Number Applications	28,822	3.55	7.44	22,722	3.57	7.15
Securing Position	28,822	0.09	0.28	22,722	0.09	0.28
Age	28,822	33.10	5.78	22,722	33.71	6.01
Time since PhD	28,822	2.89	2.85	22,722	2.82	2.78
Publish	28,822	0.64	0.48	22,722	0.49	0.50
Number Publications	28,822	5.37	18.01	22,722	2.90	11.70
Total AIS	28,822	5.85	34.76	22,722	3.29	19.44
<i>Disciplines</i>						
Biological Science	24,730	0.07	0.26	19,241	0.12	0.32
Chemical Science	24,730	0.05	0.22	19,241	0.04	0.21
Computer Science	24,730	0.11	0.31	19,241	0.04	0.21
Earth Science	24,730	0.04	0.20	19,241	0.05	0.22
Economics	24,730	0.03	0.18	19,241	0.03	0.17
Engineering	24,730	0.13	0.34	19,241	0.06	0.25
Humanities	24,730	0.18	0.38	19,241	0.31	0.46
Law and Political Science	24,730	0.05	0.22	19,241	0.06	0.23
Literature	24,730	0.05	0.21	19,241	0.12	0.32
Management Sciences	24,730	0.03	0.17	19,241	0.05	0.21
Mathematics	24,730	0.08	0.27	19,241	0.03	0.18
Philosophy and Theology	24,730	0.03	0.16	19,241	0.02	0.15
Physical Science	24,730	0.15	0.36	19,241	0.07	0.25

Notes: This table presents statistics for the key variables in the paper and the different disciplines of the qualified PhD graduates at their first year of application, if they were interested in applying for at least one position.

Table A2: Summary Statistics of Application Dataset

	Mean (1)	Std. dev. (2)	Obs (3)
Panel A: Application level			183,238
Secure position	0.024	0.155	
Female applicants	0.442	0.497	
Distance (km)	325.117	233.884	
Panel B: Job offers level			
Secured position (Sample) ^a	0.234	0.423	18,785
Secured position (Total) ^b	0.939	0.239	22,688
Number applicants per offer (Total) ^b	133.916	116.984	
Panel C: Applicant level			30,750
Female	0.452	0.498	
Secure position	0.146	0.353	
Number applications	5.959	8.261	
Age	33.475	5.808	
Time since PhD	2.521	2.605	
Number Publications	3.187	11.718	
Total AIS	2.754	20.76	

Notes: This table reports summary statistics on qualified candidate's application for junior permanent positions offers. In Panel A, I report statistics at the application level. In Panel B, I collapse the data set at the offer level. In Panel C, I collapse the data set at the applicant/qualified level.

^aRepresents the success rate in the sample of PhD graduates from France qualified and applying for at least one position the first year of qualification - the sample used in the estimation.

^bRepresents the total sample of job offers between 2009 and 2021 and the success rate among all candidates

Table A3: Gender and Success Rates Across Panel Specifications

	Panel A: Full Panel			Panel B: First Year Apply		
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	+ Controls	+ FE	Baseline	+ Controls	+ FE
female	0.00140 (0.00101)	0.000889 (0.00103)	-0.00477*** (0.00110)	0.000341 (0.00250)	-0.000475 (0.00254)	-0.00564** (0.00284)
Constant	0.0474*** (0.0007)	0.382*** (0.0139)	0.391*** (0.0156)	0.0868*** (0.0017)	0.420*** (0.0334)	0.435*** (0.0396)
Field × Univ × Year FE			Yes			Yes
Controls		Yes	Yes		Yes	Yes
Observations	181,084	181,084	178,256	51,544	51,544	47,970

Notes: *Success* is a dummy variable equal to 1 if the individual secured a permanent position. The OLS is measured at the candidate level. Column (1) includes no controls. Column (2) add applicant characteristics (age, publication volume and quality, supervisor characteristics) and Column (3) add field, year, and job univ fixed effects. Panel A represents the full population of qualified individuals and Panel B represents the restricted sample of individuals during the first year of application. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effect of Distance to Job on Hiring Probability, by Gender

	(1)	(2)	(3)
	<i>Probability of being hired</i>		
Distance (km)	-0.000132*** (0.00000648)	-0.000132*** (0.00000647)	-0.000164*** (0.00000716)
Distance ²	1.22e-07*** (8.75e-09)	1.23e-07*** (8.75e-09)	1.53e-07*** (9.64e-09)
Female	-0.00456*** (0.00150)	-0.00336** (0.00151)	-0.00281* (0.00158)
Distance × Female	0.0000173* (0.00000969)	0.0000177* (0.00000968)	0.00000488 (0.0000101)
Distance ² × Female	-1.23e-08 (1.33e-08)	-1.28e-08 (1.33e-08)	3.23e-09 (1.39e-08)
<i>Marginal effect of distance</i>			
Men	-0.000132***	-0.000132***	-0.000164***
Women	-0.000115	-0.000114	-0.000159
Women - Men	0.0000173* (0.00000969)	0.0000177* (0.00000968)	0.00000488 (0.0000101)
Controls		Yes	Yes
FE: Field, Year, Univ _j			Yes
Observations	183,238	183,238	180,874

Notes: OLS estimates of the effect of geographic distance on hiring probability, measured at the candidate-job level. Distance is the great-circle distance between the candidate's PhD institution and the job institution. The outcome is a binary Indicator equal to 1 if the candidate is hired into the position. Column (1) includes no controls. Columns (2) and (3) add applicant characteristics (age, publication volume and quality, supervisor characteristics). All models absorb field, year, and job univ fixed effects. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Additional Descriptive Statistics

B.1 Success Sample

Table B5: Descriptive Statistics - Success Sample

Variable	<i>Male</i>			<i>Female</i>		
	N	Mean	SD	N	Mean	SD
Number Applications	2,503	11.15	12.63	1,981	11.94	12.57
Age	2,503	31.79	4.87	1,981	32.51	5.18
Time since PhD	2,503	1.99	2.12	1,981	1.89	1.99
Publish	2,503	0.60	0.49	1,981	0.44	0.50
Number Publications	2,503	4.16	9.22	1,981	1.95	4.71
Total AIS	2,503	3.25	26.08	1,981	1.59	7.49
<i>Fields</i>						
Biological Science	2,503	0.03	0.18	1,981	0.04	0.19
Chemical Science	2,503	0.03	0.17	1,981	0.01	0.12
Computer Science	2,503	0.11	0.31	1,981	0.04	0.19
Earth Science	2,503	0.02	0.13	1,981	0.01	0.11
Economics	2,503	0.06	0.24	1,981	0.07	0.25
Engineering	2,503	0.13	0.33	1,981	0.05	0.22
Humanities	2,503	0.15	0.36	1,981	0.26	0.44
Law and Political Science	2,503	0.14	0.35	1,981	0.16	0.37
Literature	2,503	0.06	0.23	1,981	0.13	0.34
Management Sciences	2,503	0.09	0.28	1,981	0.14	0.34
Mathematics	2,503	0.08	0.28	1,981	0.04	0.20
Philosophy and Theology	2,503	0.01	0.10	1,981	0.01	0.11
Physical Science	2,503	0.09	0.28	1,981	0.03	0.18

Notes: This table presents statistics for the key variables in the paper and the different disciplines of the qualified PhD graduates at their first year of application, if they were interested in applying for at least one position.

B.2 Descriptive Statistics by Fields

Table B6: Descriptive Statistics - Biological & Earth Sciences

Variable	<i>Male</i>			<i>Female</i>		
	N	Mean	SD	N	Mean	SD
Apply Position	3,521	0.30	0.46	3,821	0.27	0.44
Number Applications	3,521	0.73	1.94	3,821	0.59	1.64
Securing Position	3,521	0.04	0.19	3,821	0.03	0.16
Age	3,521	32.36	3.96	3,821	31.73	3.62
Time since PhD	3,521	4.12	3.13	3,821	3.82	3.00
Publish	3,521	0.52	0.50	3,821	0.55	0.50
Number Publications	3,521	5.15	8.36	3,821	4.72	12.00
Total AIS	3,521	9.65	18.21	3,821	9.01	20.08

Notes: This table presents statistics for the key variables in the paper for the field of Biological and Earth Sciences of the qualified PhD graduates at their first year of application, if they were interested in applying for at least one position.

Table B7: Descriptive Statistics - Humanities

Variable	<i>Male</i>			<i>Female</i>		
	N	Mean	SD	N	Mean	SD
Apply Position	7,847	0.62	0.48	10,719	0.63	0.48
Number Applications	7,847	2.91	4.34	10,719	3.01	4.26
Securing Position	7,847	0.07	0.26	10,719	0.08	0.26
Age	7,847	37.30	6.99	10,719	36.22	6.70
Time since PhD	7,847	3.28	3.23	10,719	2.95	2.97
Publish	7,847	0.43	0.49	10,719	0.36	0.48
Number Publications	7,847	1.28	3.03	10,719	0.89	2.11
Total AIS	7,847	0.39	2.64	10,719	0.23	1.37

Notes: This table presents statistics for the key variables in the paper for the field of Humanities of the qualified PhD graduates at their first year of application, if they were interested in applying for at least one position.

Table B8: Descriptive Statistics - STEM

Variable	<i>Male</i>			<i>Female</i>		
	N	Mean	SD	N	Mean	SD
Apply Position	14,396	0.45	0.50	5,384	0.42	0.49
Number Applications	14,396	2.59	5.60	5,384	2.21	4.90
Securing Position	14,396	0.08	0.26	5,384	0.07	0.25
Age	14,396	30.89	3.96	5,384	30.40	3.65
Time since PhD	14,396	2.52	2.51	5,384	2.29	2.20
Publish	14,396	0.84	0.37	5,384	0.80	0.40
Number Publications	14,396	8.59	24.56	5,384	6.73	20.90
Total AIS	14,396	9.06	47.93	5,384	6.87	35.27

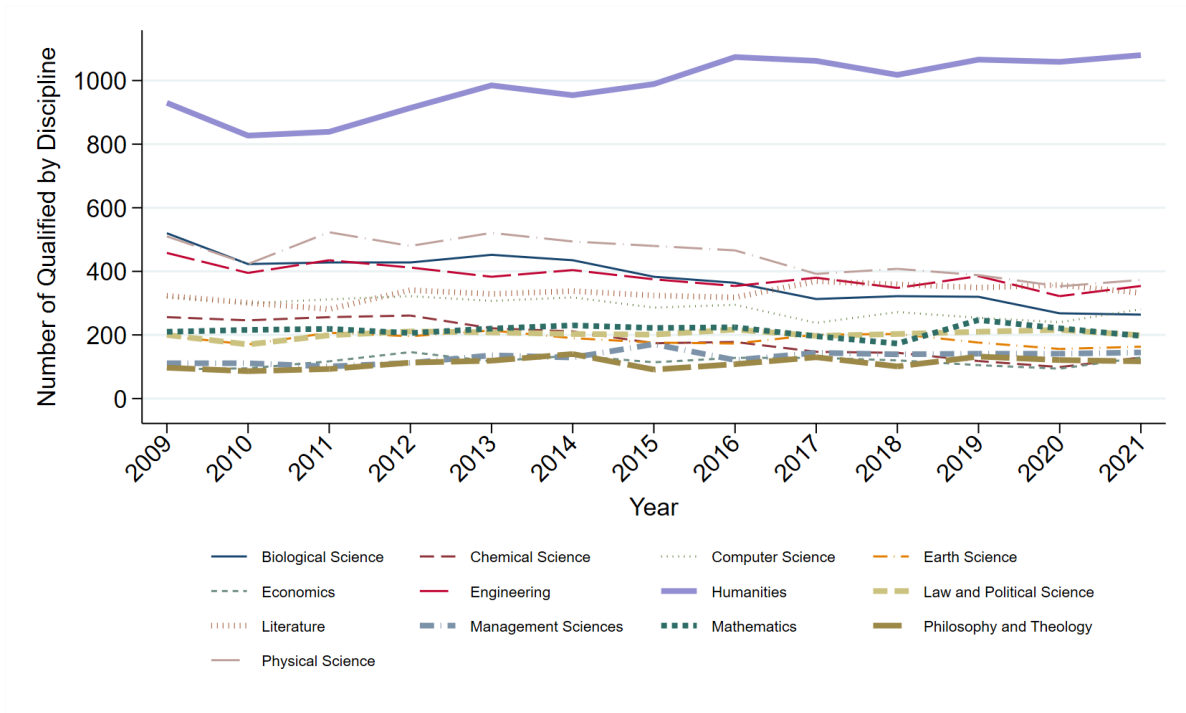
Notes: This table presents statistics for the key variables in the paper for the field of STEM of the qualified PhD graduates at their first year of application, if they were interested in applying for at least one position.

Table B9: Descriptive Statistics - Social Sciences

Variable	<i>Male</i>			<i>Female</i>		
	N	Mean	SD	N	Mean	SD
Apply Position	3,058	0.75	0.43	2,798	0.74	0.44
Number Applications	3,058	12.94	14.79	2,798	12.39	14.20
Securing Position	3,058	0.24	0.43	2,798	0.26	0.44
Age	3,058	33.58	5.33	2,798	33.15	5.16
Time since PhD	3,058	2.24	2.38	2,798	1.98	2.17
Publish	3,058	0.35	0.48	2,798	0.33	0.47
Number Publications	3,058	0.98	2.15	2,798	0.79	2.05
Total AIS	3,058	0.40	1.71	2,798	0.30	1.36

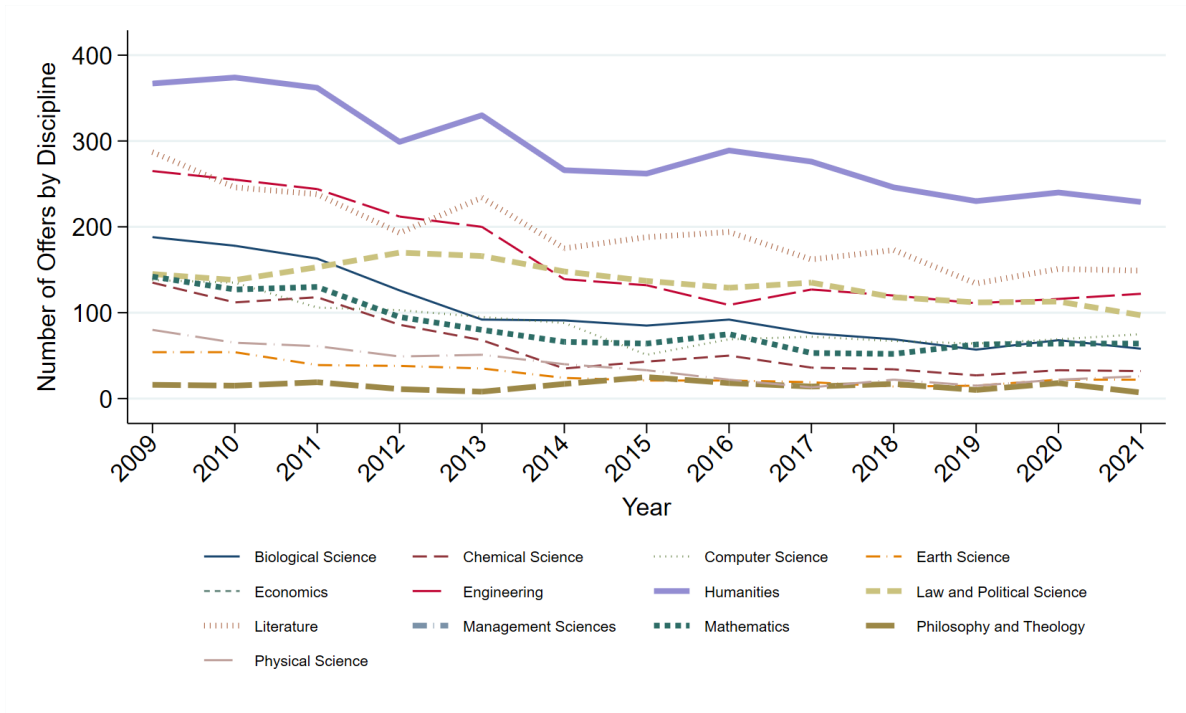
Notes: This table presents statistics for the key variables in the paper for the field of Social Sciences of the qualified PhD graduates at their first year of application, if they were interested in applying for at least one position.

Figure B7: Number of Qualified by Discipline, 2009-2021



Notes: This figure plots the annual number of qualified candidates for junior permanent position (*Maitre de Conférence*), disaggregated by discipline.

Figure B8: Number of Job Offers by Discipline, 2009-2021



Notes: This figure plots the annual number of junior position (*Maître de Conférence*) offers in French public universities, disaggregated by discipline.

B.3 Description Sub-Disciplines

Fields	Discipline	Label (fr/eng)
Law and Political Science	01	Droit privé et sciences criminelles - Private law and criminal sciences
	02	Droit public - Public law
	03	Histoire du droit et des institutions - History of law and institutions
	04	Science politique - Political Science
Economics	05	Sciences économiques
Management	06	Sciences de gestion et du management
Literature	07	Sciences du langage - Language sciences
	08	Langues et littératures anciennes - Ancient languages and literature
	09	Langue et littérature française - French language and literature
	10	Littératures comparées - Comparative literature
	11	Études anglophones - English-language studies
	12	Études germaniques et scandinaves - Germanic and Scandinavian Studies
	13	Études slaves et baltes - Slavic and Baltic Studies
	14	Études romanes - Romance languages and literature
	15	Langues, littératures et cultures africaines, asiatiques et d'autres aires linguistiques - Languages, literatures and cultures of Africa, Asia and other linguistic areas
	73	Cultures et langues régionales - Regional cultures and languages
	Humanities	16
18		Architecture (ses théories et ses pratiques), arts appliqués, arts plastiques, arts du spectacle, épistémologie des enseignements artistiques, esthétique, musicologie, musique, sciences de l'art - Arts
19		Sociologie, démographie - Sociology, demography
20		Ethnologie, préhistoire, anthropologie biologique - Biological anthropology, ethnology, prehistory
21		Histoire, civilisations, archéologie et art des mondes anciens et médiévaux - History, civilization: archaeology, art of ancient worlds
22		Histoire et civilisations : histoire des mondes modernes, histoire du monde contemporain ; de l'art ; de la musique - History, civilizations: history of modern worlds
23		Géographie physique, humaine, économique et régionale - Physical, human, economic and regional geography
24		Aménagement de l'espace, urbanisme - Spatial planning and urban development
70		Sciences de l'éducation et de la formation - Education sciences
71		Sciences de l'information et de la communication - Information and communication sciences
72		Épistémologie, histoire des sciences et des techniques - Epistemology, history of science and technology
Mathematics	25	Mathématiques - Mathematics
	26	Mathématiques appliquées et applications des mathématiques - Applied mathematics and mathematical applications
Computer Science	27	Informatique - Computer science
Physical Science	28	Milieux denses et matériaux - Dense media and materials
	29	Constituants élémentaires - Elementary constituents
	30	Milieux dilués et optique - Diluted media and optics
Chemical Science	31	Chimie théorique, physique, analytique - Theoretical, physical and analytical chemistry
	32	Chimie organique, minérale, industrielle - Organic, inorganic and industrial chemistry
	33	Chimie des matériaux - Materials chemistry
Earth Science	34	Astronomie, astrophysique - Astronomy, astrophysics
	35	Structure et évolution de la terre et des autres planètes - Structure and evolution of the Earth and other planets
	36	Terre solide : géodynamique des enveloppes supérieure, paléobiosphère - Solid Earth: geodynamics of the upper envelope
	37	Enveloppes fluides du système Terre et autres planètes - Fluid envelopes of the Earth system and other planets
Engineering	60	Mécanique, génie mécanique, génie civil - Mechanical engineering, civil engineering
	61	Génie informatique, automatique et traitement du signal - Computer engineering, automation and signal processing
	62	Energétique, génie des procédés - Energy and process engineering
	63	Génie électrique, électronique, photonique et systèmes - Electrical engineering, electronics, photonics and systems
Biological Science	64	Biochimie et biologie moléculaire - Biochemistry and molecular biology
	65	Biologie cellulaire - Cell Biology
	66	Physiologie - Physiology
	67	Biologie des populations et écologie - Population biology and ecology
	68	Biologie des organismes - Organismal biology
	69	Neurosciences - Neuroscience
Philosophy and Theology	76	Théologie catholique - Catholic theology
	77	Théologie protestante - Protestant theology
	17	Philosophie - Philosophy
Medical Science	85	Personnels enseignants-chercheurs de pharmacie en sciences physico-chimiques et ingénierie appliquée à la santé - Engineering applied to health
	86	Personnels enseignants-chercheurs de pharmacie en sciences du médicament et des autres produits de santé - Sciences of drugs and other health products
	87	Personnels enseignants-chercheurs de pharmacie en sciences biologiques, fondamentales et cliniques - Biological, fundamental and clinical sciences
	90	Maïeutique - Maieutics
	91	Personnels enseignants-chercheurs des disciplines des sciences de la rééducation et de réadaptation - Rehabilitation sciences
	92	Personnels enseignants-chercheurs des disciplines des sciences infirmières - Nursing
	74	Sciences et techniques des activités physiques et sportives - Sciences and techniques of physical activities and sports

Table B10: CNU Sections and Labels

C Methodology

C.1 Construction of the Commuting Time Variable

To complement great-circle distance as a measure of geographic frictions, I construct a variable for estimated commuting time between the PhD institution and the job location. This variable is designed to better capture realistic travel costs faced by candidates, accounting for transportation infrastructure and regional accessibility.

The commuting time is computed in several steps:

1. **Train-based commuting time.** I merge the dyadic dataset with an external dataset containing average train travel times between French cities, using information from the French national railway open data platform (data.sncf.com). The merge is based on year and city-to-city routes (e.g., “Lyon–Paris”).
2. **Special adjustments for the Paris region.** For movements within the Île-de-France region, where suburban candidates frequently commute to central Paris, I assign a default value of 60 minutes, reflecting typical intra-regional commuting durations. This value is applied to both directions (from/to Paris). In a second step, I redefine all cities within Île-de-France as “Paris” to capture additional matches in the train time dataset. I re-merge the data and add 60 minutes to the retrieved travel time to account for average commuting from the broader metropolitan area.
3. **Fallback proxy using road travel time.** For remaining unmatched observations, I impute commuting time using a road-based proxy derived from great-circle distance. Assuming a speed of 90 km/h and inflating the straight-line distance by a factor of 1.2, I approximate round-trip travel time as follows:

$$\text{Commuting Time (min)} = 2 \times \left(\frac{1.2 \times \text{Distance (km)}}{90} \right) \times 60$$

This provides a conservative estimate of round-trip driving time.

D Robustness

D.1 Candidate-Job Dyads Level Application Behavior

Table [D11](#): Application Patterns by Candidate-Job Dyads - Distance in km

Table [D12](#): Application Patterns by Candidate-Job Dyads - Commuting Time

Table [D13](#): Application Patterns by Candidate-Job Dyads - controls: age at PhD and time since graduation

Table [D14](#): Application Patterns by Candidate-Job Dyads - Excluding Paris candidates

Table [D15](#): Application Patterns by Candidate-Job Dyads - Subsamples Based on Application Timing

Table [D16](#): Application Patterns by Candidate-Job Dyads - Heterogeneity by Field

Table [D17](#): Application Patterns by Candidate-Job Dyads - Heterogeneity Analysis

D.2 Individual-level Application Behavior

Table [D18](#): Gender Differences in Application Patterns by Distance to Job Offers - Pseudo-Maximum Likelihood

Table [D19](#): Application Patterns by Commuting Time to Job Offers

Table [D20](#): Application Patterns by Distance to Job Offers Controlling for age at PhD graduation and time since PhD graduation

Table [D21](#): Application Patterns by Distance to Job Offers - Excluding Paris

Table [D22](#): Application Patterns by Distance to Job Offers - subsamples based on application timing

Table [D23](#): Application Patterns by Distance to Job Offers – by Field

Table [D24](#): Application Patterns by Geography of Job Offers – Same City vs Same Region

D.1 Candidate-Job Dyads Level Application Behavior

Table D11: Application Patterns by Candidate-Job Dyads - Distance in km

	(1)	(2)	(3)
Dependent variable:	<i>Apply to position</i>		
Female	0.00197 (0.00183)	-0.00277 (0.00203)	- -
Distance (km)	-0.0000748*** (0.00000199)	- -	-0.0000744*** (0.00000186)
Distance (km) × Female	-0.0000206*** (0.00000294)	-0.00000749** (0.00000379)	-0.0000216*** (0.00000259)
Adj R^2	0.19	0.20	0.30
Controls	yes	yes	yes
Fixed effects	$U_i \times t \times d + U_j \times t \times d$	$U_i \times U_j \times t \times d$	$i \times (t \times d) + j \times (t \times d)$
Observations	2,287,422	2,162,136	2,286,953

Notes: *Apply* is a binary variable equal to 1 if the candidate applied to a specific job. Each observation represents a dyad between a candidate and a potential job opening. *Distance* is the geographical distance between the job and the candidate’s PhD institution. All regressions include controls for age, publication metrics, and a dummy equal to 1 if at least one PhD supervisor is female. Fixed effects vary across specifications and are indicated in the “Fixed effects” row: U_i denotes the university of candidate i , U_j the university of the job j , t the year, and f the field. i and j denote candidate and job identifiers, respectively. Standard errors are clustered by Field X PhD Univ X Year. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D12: Application Patterns by Candidate-Job Dyads - Commuting Time

	(1)	(2)	(3)
Dependent variable:	<i>Apply to position</i>		
Female	0.00123 (0.00178)	-0.00292 (0.00195)	- -
Commuting time (min)	-0.000127*** (0.00000364)	- -	-0.000124*** (0.00000333)
Commuting time (min) × Female	-0.0000346*** (0.00000517)	-0.0000132** (0.00000662)	-0.0000429*** (0.00000413)
Adj R^2	0.19	0.20	0.30
Controls	yes	yes	yes
Fixed effects	$U_i \times t \times d + U_j \times t \times d$	$U_i \times U_j \times t \times d$	$i \times (t \times d) + j \times (t \times d)$
Observations	2,287,422	2,162,136	2,286,968

Notes: *Apply* is a binary variable equal to 1 if the candidate applied to a specific job. Each observation represents a dyad between a candidate and a potential job opening. *Commuting time* combines train travel time (from official SNCF timetables), road travel time (based on routing algorithms), and AI-based predictions for less connected pairs. Details of the construction are provided in Appendix Section C.1@. between the job and the candidate’s PhD institution. All regressions include controls for age, publication metrics, and a dummy equal to 1 if at least one PhD supervisor is female. Fixed effects vary across specifications and are indicated in the “Fixed effects” row: U_i denotes the university of candidate i , U_j the university of the job j , t the year, and f the field. i and j denote candidate and job identifiers, respectively. Standard errors are clustered by Field X PhD Univ X Year. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D13: Application Patterns by Candidate-Job Dyads - controls: age at PhD and time since graduation

	(1)	(2)
Dependent variable:	<i>Apply to position</i>	
Female	0.00710** (0.00279)	0.000582 (0.00323)
ln(Distance)	-0.0127*** (0.000319)	- -
ln(Distance) × Female	-0.00236*** (0.000439)	-0.00113** (0.000533)
Adj R^2	0.19	0.20
Controls	yes	yes
Fixed effects	$U_i \times t \times d + U_j \times t \times d$	$U_i \times U_j \times t \times d$
Observations	2,287,422	2,162,136

Notes: *Apply* is a binary variable equal to 1 if the candidate applied to a specific job. Each observation represents a dyad between a candidate and a potential job opening. $\ln(\text{Distance})$ is the logarithm of the geographical distance between the job and the candidate's PhD institution. All regressions include controls for age, publication metrics, and a dummy equal to 1 if at least one PhD supervisor is female. Fixed effects vary across specifications and are indicated in the "Fixed effects" row: U_i denotes the university of candidate i , U_j the university of the job j , t the year, and f the field. i and j denote candidate and job identifiers, respectively. Standard errors are clustered by Field X PhD Univ X Year. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D14: Application Patterns by Candidate-Job Dyads - Excluding Paris candidates

	(1)	(2)	(3)
Dependent variable:	<i>Apply to position</i>		
Female	0.0208*** (0.00436)	0.000107 (0.00510)	- -
ln(Distance)	-0.0154*** (0.000409)	- -	-0.0153*** (0.000397)
ln(Distance) × Female	-0.00482*** (0.000686)	-0.00118 (0.000837)	-0.00513*** (0.000651)
Adj R^2	0.20	0.21	0.30
Controls	yes	yes	yes
Fixed effects	$U_i \times t \times d + U_j \times t \times d$	$U_i \times U_j \times t \times d$	$i \times (t \times d) + j \times (t \times d)$
Observations	1,576,906	1,470,253	1,576,684

Notes: *Apply* is a binary variable equal to 1 if the candidate applied to a specific job. Each observation represents a dyad between a candidate and a potential job opening. $\ln(\text{Distance})$ is the logarithm of the geographical distance between the job and the candidate's PhD institution. All regressions include controls for age, publication metrics, and a dummy equal to 1 if at least one PhD supervisor is female. Fixed effects vary across specifications and are indicated in the "Fixed effects" row: U_i denotes the university of candidate i , U_j the university of the job j , t the year, and f the field. i and j denote candidate and job identifiers, respectively. Qualified candidates from Paris are excluded. Standard errors are clustered by Field X PhD Univ X Year. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D15: Application Patterns by Candidate-Job Dyads - Subsamples Based on Application Timing

	(1)	(2)	(3)
	<i>Apply to position</i>		
Panel A: Candidates who applied at least once in their career			
Female	0.00771** (0.00334)	0.00174 (0.00390)	- -
ln(Distance)	-0.0171*** (0.00040)	- -	-0.0172*** (0.00039)
ln(Distance) × Female	-0.00255*** (0.00054)	-0.00139** (0.00066)	-0.00249*** (0.00050)
Adj R^2	0.20	0.20	0.30
Observations	1,726,884	1,601,520	1,726,649
Panel B: Candidates who applied in year of first qualification			
Female	0.00692* (0.00371)	0.00111 (0.00438)	- -
ln(Distance)	-0.0214*** (0.00048)	- -	-0.0214*** (0.00047)
ln(Distance) × Female	-0.00246*** (0.00062)	-0.00132* (0.00078)	-0.00263*** (0.00060)
Adj R^2	0.20	0.21	0.28
Observations	1,390,720	1,272,226	1,390,599
Panel C: Second year after qualification			
Female	0.00391 (0.00252)	0.00196 (0.00294)	- -
ln(Distance)	-0.00677*** (0.00023)	- -	-0.00687*** (0.00021)
ln(Distance) × Female	-0.00157*** (0.00037)	-0.00118*** (0.00045)	-0.00133*** (0.00030)
Adj R^2	0.147	0.132	0.297
Observations	2,021,493	1,907,890	2,020,987
Panel D: Third year after qualification			
Female	0.00109 (0.00209)	-0.00035 (0.00249)	- -
ln(Distance)	-0.00435*** (0.00019)	- -	-0.00432*** (0.00018)
ln(Distance) × Female	-0.00091*** (0.00031)	-0.00062 (0.00040)	-0.00098*** (0.00025)
Adj R^2	0.120	0.102	0.273
Observations	1,764,522	1,662,447	1,764,043
Panel E: Fourth year after qualification			
Female	-0.00006 (0.00165)	-0.00306 (0.00194)	- -
ln(Distance)	-0.00289*** (0.00016)	- -	-0.00281*** (0.00015)
ln(Distance) × Female	-0.00043* (0.00024)	0.00015 (0.00030)	-0.00061*** (0.00021)
Adj R^2	0.099	0.076	0.248
Observations	1,524,331	1,434,473	1,523,912
Controls	yes	yes	yes
Fixed effects	$U_i \times t \times d + U_j \times t \times d$	$U_i \times U_j \times t \times d$	$i \times (t \times d) + j \times (t \times d)$

Notes: *Apply* is a binary variable equal to 1 if the candidate applied to a specific job. Each observation represents a dyad between a candidate and a potential job opening. $\ln(\text{Distance})$ is the logarithm of the geographical distance between the job and the candidate's PhD institution. All regressions include controls for age, publication metrics, and a dummy equal to 1 if at least one PhD supervisor is female. Fixed effects vary across specifications and are indicated above. Standard errors are clustered by Field X PhD Univ X Year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D16: Application Patterns by Candidate-Job Dyads - Heterogeneity by Field

	(1)	(2)	(3)
	<i>Apply to position</i>		
Panel A: Qualified in biological and earth sciences			
Female	0.00039 (0.00401)	0.00079 (0.00464)	- -
ln(Distance)	-0.00790*** (0.00055)	- -	-0.00788*** (0.00057)
ln(Distance) × Female	-0.00058 (0.00066)	-0.00062 (0.00077)	-0.00062 (0.00068)
Adj R^2	0.08	0.09	0.13
Observations	245,228	220,687	244,527
Panel B: Qualified in humanities			
Female	-0.00468 (0.00385)	-0.00687 (0.00429)	- -
ln(Distance)	-0.0121*** (0.00056)	- -	-0.0122*** (0.00054)
ln(Distance) × Female	-0.00071 (0.00062)	-0.00020 (0.00072)	-0.00054 (0.00060)
Adj R^2	0.09	0.09	0.18
Observations	611,387	569,559	609,639
Panel C: Qualified in STEM			
Female	0.00999** (0.00465)	0.00701 (0.00543)	- -
ln(Distance)	-0.0100*** (0.00036)	- -	-0.00998*** (0.00035)
ln(Distance) × Female	-0.00211*** (0.00074)	-0.00157* (0.00089)	-0.00223*** (0.00064)
Adj R^2	0.10	0.10	0.21
Observations	1,045,478	987,343	1,044,110
Panel D: Qualified in social sciences			
Female	0.0128 (0.0103)	0.00974 (0.0119)	- -
ln(Distance)	-0.0255*** (0.00126)	- -	-0.0263*** (0.00116)
ln(Distance) × Female	-0.00454*** (0.00160)	-0.00409** (0.00195)	-0.00289** (0.00136)
Adj R^2	0.27	0.28	0.41
Observations	382,761	362,659	381,733
Controls	yes	yes	yes
Fixed effects	$U_i \times t \times d + U_j \times t \times d$	$U_i \times U_j \times t \times d$	$i \times (t \times d) + j \times (t \times d)$

Notes: *Apply* is a binary variable equal to 1 if the candidate applied to a specific job. Each observation represents a dyad between a candidate and a potential job opening. $\ln(\text{Distance})$ is the logarithm of the geographical distance between the job and the candidate's PhD institution. All regressions include controls for age, publication metrics, and a dummy equal to 1 if at least one PhD supervisor is female. Fixed effects vary across specifications and are indicated in the original field-specific tables. Standard errors are clustered by Field X PhD Univ X Year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D17: Application Patterns by Candidate-Job Dyads - Heterogeneity Analysis

	(1)	(2)
Dependent variable:	<i>Apply to position</i>	
Age	\geq median	$<$ median
$\ln(\text{Distance})$	-0.0121*** (0.000433)	-0.0131*** (0.000379)
$\ln(\text{Distance}) \times \text{Female}$	-0.00303*** (0.000645)	-0.00186*** (0.000494)
Years since PhD	\geq median	$<$ median
$\ln(\text{Distance})$	-0.00988*** (0.000348)	-0.0149*** (0.000449)
$\ln(\text{Distance}) \times \text{Female}$	-0.00150*** (0.000496)	-0.00288*** (0.000585)
Total AIS	$= 0$	> 0
$\ln(\text{Distance})$	-0.0155*** (0.000474)	-0.0100*** (0.000347)
$\ln(\text{Distance}) \times \text{Female}$	-0.00197*** (0.000563)	-0.00149*** (0.000519)
Number Publications	$= 0$	> 0
$\ln(\text{Distance})$	-0.0170*** (0.000589)	-0.0104*** (0.000310)
$\ln(\text{Distance}) \times \text{Female}$	-0.00117* (0.000675)	-0.00207*** (0.000469)
Controls, FE	yes	yes

Notes: *Apply* is a binary variable equal to 1 if the candidate applied to a specific job. Each observation represents a dyad between a candidate and a potential job opening. $\ln(\text{Distance})$ is the logarithm of the geographical distance between the job and the candidate's PhD institution. All regressions include controls for age, publication metrics, and a dummy equal to 1 if at least one PhD supervisor is female. Fixed effects vary across Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Individual-level Application Behavior

Table D18: Gender Differences in Application Patterns by Distance to Job Offers - Pseudo-Maximum Likelihood

Dependent variable:	<i>Applications to Nearby Jobs ($\leq 100\text{km}$)</i>			<i>Applications to Distant Jobs ($>100\text{km}$)</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Near Apps</i>	<i>Near Apps</i>	<i>Near Apps</i>	<i>Near Apps</i>	<i>Near Apps</i>	<i>Near Apps</i>
Female	-0.0528** (0.0241)	-0.0639*** (0.0240)	-0.0532** (0.0259)	-0.0712** (0.0285)	-0.0917*** (0.0284)	-0.102*** (0.0283)
Near offers	0.0939*** (0.00206)	0.0942*** (0.00206)	0.0755*** (0.00444)			
Female \times Near offers	0.00506*** (0.00184)	0.00531*** (0.00183)	0.00351* (0.00205)			
Far offers				0.0297*** (0.00131)	0.0291*** (0.00130)	0.0163*** (0.00316)
Female \times Far offers				-0.0000862 (0.000672)	0.0000112 (0.000663)	0.000114 (0.000649)
Controls		yes	yes		yes	yes
Fields X Year FE	yes	yes	yes	yes	yes	yes
Fields X Univ PhD FE			yes			yes
Observations	66628	66628	57979	67824	67824	64992

Notes: The dependent variable is the number of applications, submitted by candidates, separately for nearby job offers (within 100km) and distant job offers (over 100km). Control variables include age, publication metrics, a dummy equal to 1 if at least one PhD supervisor is female, and supervisor productivity and number of offers. Estimated using Poisson Pseudo-Maximum Likelihood (PPML) regression. Standard errors are clustered by Field X PhD Univ X Year. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D19: Application Patterns by Commuting Time to Job Offers

Dependent variable:	<i>Applications to Nearby Jobs ($\leq 90min$)</i>			<i>Applications to Distant Jobs ($>90min$)</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Near Apps</i>	<i>Near Apps</i>	<i>Near Apps</i>	<i>Near Apps</i>	<i>Near Apps</i>	<i>Near Apps</i>
Female	-0.0224*** (0.00466)	-0.0252*** (0.00467)	-0.0103** (0.00455)	-0.0342*** (0.00812)	-0.0403*** (0.00812)	-0.0315*** (0.00842)
Near offers	0.0232*** (0.000623)	0.0232*** (0.000625)	0.0217*** (0.000954)			
Female \times Near offers	0.00274*** (0.000703)	0.00280*** (0.000701)	0.000536 (0.000709)			
Far offers				0.0150*** (0.000508)	0.0148*** (0.000506)	0.00863*** (0.00115)
Female \times Far offers				0.000109 (0.000366)	0.000108 (0.000364)	-0.000280 (0.000374)
Controls		yes	yes		yes	yes
Fields X Year FE	yes	yes	yes	yes	yes	yes
Fields X Univ PhD FE			yes			yes
Observations	68258	68258	67617	68258	68258	67617

Notes: The dependent variable is the number of applications, submitted by candidates, separately for nearby job offers (within 90min of commuting time) and distant job offers (over 90min of commuting time). Control variables include age, publication metrics, a dummy equal to 1 if at least one PhD supervisor is female, and supervisor productivity and number of offers. Standard errors are clustered by Field X PhD Univ X Year. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D20: Application Patterns by Distance to Job Offers Controlling for age at PhD graduation and time since PhD graduation

	<i>Applications to Nearby Jobs ($\leq 100\text{km}$)</i>		<i>Applications to Distant Jobs ($>100\text{km}$)</i>	
	(1)	(2)	(3)	(4)
Dependent variable:	$\ln(\text{near apps} + 1)$	$\ln(\text{near apps} + 1)$	$\ln(\text{near apps} + 1)$	$\ln(\text{far apps} + 1)$
Female	-0.0228*** (0.00404)	-0.00908** (0.00412)	-0.0341*** (0.00867)	-0.0319*** (0.00896)
Near offers	0.0280*** (0.000789)	0.0299*** (0.00124)		
Female \times Near offers	0.00455*** (0.000964)	0.00131 (0.00101)		
Far offers			0.0172*** (0.000730)	0.0107*** (0.00154)
Female \times Far offers			-0.0000998 (0.000348)	-0.000258 (0.000356)
Adj R-squared	0.33	0.38	0.34	0.35
Controls	yes	yes	yes	yes
Fields X Year FE	yes	yes	yes	yes
Fields X Univ PhD FE		yes		yes
Observations	68258	67617	68258	67617

Notes: The dependent variable is the natural logarithm of the number of applications plus one, submitted by candidates, separately for nearby job offers (within 100km) and distant job offers (over 100km). Control variables include age at PhD defense, time since PhD graduation, publication metrics, a dummy equal to 1 if at least one PhD supervisor is female, and supervisor productivity and number of offers. Standard errors are clustered by Field X PhD Univ X Year. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D21: Application Patterns by Distance to Job Offers - Excluding Paris

Dependent variable:	<i>Applications to Nearby Jobs ($\leq 100\text{km}$)</i>			<i>Applications to Distant Jobs ($>100\text{km}$)</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(\text{near apps} + 1)$	$\ln(\text{near apps} + 1)$	$\ln(\text{near apps} + 1)$	$\ln(\text{far apps} + 1)$	$\ln(\text{far apps} + 1)$	$\ln(\text{far apps} + 1)$
Female	-0.0183*** (0.00414)	-0.0194*** (0.00418)	-0.00876** (0.00428)	-0.0368*** (0.0112)	-0.0454*** (0.0112)	-0.0441*** (0.0117)
Near offers	0.0270*** (0.00118)	0.0270*** (0.00118)	0.0397*** (0.00184)			
Female \times Near offers	0.00631*** (0.00176)	0.00635*** (0.00176)	0.00152 (0.00179)			
Far offers				0.0159*** (0.00124)	0.0160*** (0.00124)	0.00738*** (0.00242)
Female \times Far offers				0.0000701 (0.000419)	0.000107 (0.000416)	-0.000107 (0.000427)
Adj R-squared	0.26	0.25	0.30	0.32	0.33	0.35
Controls		yes	yes		yes	yes
Fields X Year FE	yes	yes	yes	yes	yes	yes
Fields X Univ PhD FE			yes			yes
Observations	45385	45385	44882	45385	45385	44882

Notes: The dependent variable is the natural logarithm of the number of applications plus one, submitted by candidates, separately for nearby job offers (within 100km) and distant job offers (over 100km). Control variables include age, publication metrics, a dummy equal to 1 if at least one PhD supervisor is female, and supervisor productivity and number of offers. This sample exclude candidates from Paris. Standard errors are clustered by Field X PhD Univ X Year. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D22: Application Patterns by Distance to Job Offers - subsamples based on application timing

Dependent variable:	<i>Applications to Nearby Jobs ($\leq 100\text{km}$)</i>			<i>Applications to Distant Jobs ($>100\text{km}$)</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>ln(near apps + 1)</i>			<i>ln(far apps + 1)</i>		
Panel A: Applied at least once in career						
Female	-0.0164*** (0.00495)	-0.0198*** (0.00497)	-0.00613 (0.00512)	-0.0183* (0.0107)	-0.0283*** (0.0107)	-0.0237** (0.0113)
Near offers	0.0392*** (0.00089)	0.0393*** (0.00089)	0.0384*** (0.00145)			
Female \times Near offers	0.00421*** (0.00105)	0.00431*** (0.00105)	0.00098 (0.00109)			
Far offers				0.0198*** (0.00083)	0.0196*** (0.00082)	0.0140*** (0.00180)
Female \times Far offers				-0.00047 (0.00039)	-0.00050 (0.00039)	-0.00073* (0.00040)
Adj R^2	0.40	0.40	0.45	0.37	0.37	0.39
Observations	49,648	49,648	48,959	49,648	49,648	48,959
Panel B: Applied at least once in first year of qualification						
Female	-0.0133** (0.00626)	-0.0151** (0.00628)	-0.00347 (0.00634)	-0.0301** (0.0120)	-0.0372*** (0.0120)	-0.0317** (0.0130)
Near offers	0.0476*** (0.00099)	0.0476*** (0.00099)	0.0440*** (0.00159)			
Female \times Near offers	0.00288** (0.00115)	0.00296** (0.00115)	0.00031 (0.00116)			
Far offers				0.0250*** (0.00085)	0.0248*** (0.00085)	0.0210*** (0.00192)
Female \times Far offers				-0.00048 (0.00039)	-0.00048 (0.00039)	-0.00071* (0.00041)
Adj R^2	0.46	0.45	0.50	0.50	0.41	0.41
Observations	37,755	37,755	36,987	37,755	37,755	36,987
Controls		yes	yes		yes	yes
Fields \times Year FE	yes	yes	yes	yes	yes	yes
Fields \times Univ PhD FE			yes			yes

Notes: The dependent variable is the natural logarithm of the number of applications plus one, separately for nearby jobs (within 100km) and distant jobs (over 100km). Control variables include age, publication metrics, a dummy equal to 1 if at least one PhD supervisor is female, and supervisor productivity and number of offers. Panel A includes candidates who applied at least once in their career. Panel B includes those who applied in the first year of qualification. Standard errors are clustered by Field X PhD Univ X Year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D23: Application Patterns by Distance to Job Offers – by Field

	<i>Applications to Nearby Jobs ($\leq 100km$)</i>			<i>Applications to Distant Jobs ($>100km$)</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Biological and Earth Sciences						
Female	-0.00437 (0.00380)	-0.00297 (0.00380)	-0.00501 (0.00405)	-0.0258** (0.0115)	-0.0236** (0.0116)	-0.0180 (0.0114)
Near offers	0.0105*** (0.00147)	0.0105*** (0.00147)	0.0181*** (0.00229)			
Female \times Near offers	0.00234 (0.00179)	0.00224 (0.00178)	0.00246 (0.00195)			
Far offers				0.00834*** (0.00130)	0.00824*** (0.00130)	0.00280 (0.00224)
Female \times Far offers				-0.00042 (0.00071)	-0.00043 (0.00071)	-0.00037 (0.00071)
Adj R^2	0.07	0.07	0.08	0.06	0.07	0.10
Observations	12,531	12,531	12,200	12,531	12,531	12,200
Panel B: Humanities						
Female	-0.00233 (0.00631)	-0.00064 (0.00631)	-0.00112 (0.00676)	-0.0384*** (0.0139)	-0.0326** (0.0139)	-0.0348** (0.0148)
Near offers	0.0200*** (0.00090)	0.0201*** (0.00091)	0.0240*** (0.00168)			
Female \times Near offers	0.00212 (0.00155)	0.00206 (0.00155)	0.00156 (0.00160)			
Far offers				0.0155*** (0.00096)	0.0154*** (0.00095)	0.00736*** (0.00221)
Female \times Far offers				0.00055 (0.00046)	0.00051 (0.00046)	0.00035 (0.00048)
Adj R^2	0.17	0.17	0.20	0.15	0.15	0.17
Observations	26,485	26,485	26,075	26,485	26,485	26,075
Panel C: STEM						
Female	-0.0133** (0.00626)	-0.0151** (0.00628)	-0.00347 (0.00634)	-0.0301** (0.0120)	-0.0372*** (0.0120)	-0.0317** (0.0130)
Near offers	0.0476*** (0.00099)	0.0476*** (0.00099)	0.0440*** (0.00159)			
Female \times Near offers	0.00288** (0.00115)	0.00296** (0.00115)	0.00031 (0.00116)			
Far offers				0.0250*** (0.00085)	0.0248*** (0.00085)	0.0210*** (0.00192)
Female \times Far offers				-0.00048 (0.00039)	-0.00048 (0.00039)	-0.00071* (0.00041)
Adj R^2	0.46	0.45	0.50	0.50	0.41	0.41
Observations	37,755	37,755	36,987	37,755	37,755	36,987
Panel D: Social Sciences						
Female	-0.00112 (0.0237)	-0.00822 (0.0237)	-0.0113 (0.0232)	-0.0613 (0.0470)	-0.0606 (0.0464)	-0.0651 (0.0514)
Near offers	0.0478*** (0.00235)	0.0484*** (0.00234)	0.0409*** (0.00449)			
Female \times Near offers	0.00080 (0.00295)	0.00104 (0.00294)	0.00105 (0.00285)			
Far offers				0.0290*** (0.00219)	0.0278*** (0.00215)	0.0141** (0.00569)
Female \times Far offers				0.00001 (0.00094)	-0.00035 (0.00092)	-0.00043 (0.00098)
Adj R^2	0.36	0.37	0.44	0.28	0.30	0.32
Observations	6,477	6,477	6,262	6,477	6,477	6,262
Controls		yes	yes		yes	yes
Fields \times Year FE	yes	yes	yes	yes	yes	yes
Fields \times Univ PhD FE			yes			yes

Notes: The dependent variable is the natural logarithm of the number of applications plus one, separately for nearby job offers ($\leq 100km$) and distant job offers ($>100km$). All regressions include controls for age, publication metrics, a dummy equal to 1 if at least one PhD supervisor is female, and supervisor productivity and number of offers. Each panel restricts the sample to candidates in a specific field. Standard errors are clustered by Field \times PhD Univ \times Year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D24: Application Patterns by Geography of Job Offers – Same City vs Same Region

Panel A: Same City						
Dependent variable:	Applications to Jobs in Same City			Applications to Jobs Outside City		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(\text{city apps} + 1)$	$\ln(\text{city apps} + 1)$	$\ln(\text{city apps} + 1)$	$\ln(\text{non-city apps} + 1)$	$\ln(\text{non-city apps} + 1)$	$\ln(\text{non-city apps} + 1)$
Female	-0.0121*** (0.00338)	-0.0133*** (0.00338)	-0.00472 (0.00334)	-0.0301*** (0.00877)	-0.0370*** (0.00877)	-0.0352*** (0.00910)
Same-city offers	0.0357*** (0.00108)	0.0358*** (0.00108)	0.0352*** (0.00147)			
Female × Same-city offers	0.00417*** (0.00120)	0.00420*** (0.00120)	0.00140 (0.00122)			
Outside-city offers				0.0179*** (0.00089)	0.0176*** (0.00088)	0.0117*** (0.00183)
Female × Outside-city offers				0.00006 (0.00034)	0.00007 (0.00033)	-0.00009 (0.00034)
Adj R^2	0.35	0.35	0.40	0.33	0.33	0.35
Observations	68,258	68,258	67,617	68,258	68,258	67,617
Panel B: Same Region						
Dependent variable:	Applications to Jobs in Same Region			Applications to Jobs Outside Region		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(\text{region apps} + 1)$	$\ln(\text{region apps} + 1)$	$\ln(\text{region apps} + 1)$	$\ln(\text{outside-region apps} + 1)$	$\ln(\text{outside-region apps} + 1)$	$\ln(\text{outside-region apps} + 1)$
Female	-0.0234*** (0.00453)	-0.0258*** (0.00454)	-0.0146*** (0.00474)	-0.0240*** (0.00859)	-0.0308*** (0.00860)	-0.0303*** (0.00889)
Same-region offers	0.0270*** (0.00082)	0.0271*** (0.00082)	0.0292*** (0.00123)			
Female × Same-region offers	0.00419*** (0.00099)	0.00426*** (0.00099)	0.00181* (0.00104)			
Outside-region offers				0.0174*** (0.00081)	0.0172*** (0.00080)	0.0114*** (0.00153)
Female × Outside-region offers				-0.00023 (0.00035)	-0.00021 (0.00035)	-0.00033 (0.00036)
Adj R^2	0.34	0.34	0.37	0.32	0.33	0.35
Observations	68,258	68,258	67,617	68,258	68,258	67,617
Controls		yes	yes		yes	yes
Fields × Year FE	yes	yes	yes	yes	yes	yes
Fields × Univ PhD FE			yes			yes

Notes: The dependent variable is the natural logarithm of the number of applications plus one. "Same-unit" applications refer to those submitted to jobs in the same city (Panel A) or same administrative region (Panel B) as the candidate's PhD institution. "Outside-unit" refers to all other locations. All regressions include controls for age, publication metrics, a dummy equal to 1 if at least one PhD supervisor is female, and supervisor productivity and number of offers. Standard errors are clustered by Field X PhD Univ X Year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.