Occupational Mobility and Retraining

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Monday 17th March, 2025

Abstract

This paper studies constraints to occupational mobility, distinguishing between "frictional mismatch" (job seekers not directing their search towards occupations and firms with high hiring potential) and "skills mismatch" (a gap between workers' training or experience and the demands of firms). In a large-scale correspondence study, we investigate the effectiveness of retraining programs in enabling workers to transition into high-demand occupations. Sending more than 5,000 fictitious job applications to employers in France for positions in six high-demand occupations, we randomly manipulate candidates' training and experience. We show that compared to an *incumbent* candidate with both initial training and experience in the target occupation, callback rates vary substantially for three movers initially trained and employed in neighboring, less constrained occupations, each with different levels of retraining for the target occupation. While incumbents receive the highest callback rate (56%), this is closely followed by *long-retraining movers*, who completed several weeks or months of retraining. In contrast, *short-retraining movers* and *untrained movers* receive significantly fewer callbacks. We develop and validate a matching model, which predicts that the effect of retraining on callbacks should increase and then decrease with labor market tightness. Using geographic variation in tightness, we find that even in the high-demand labor markets studied, the effect of retraining on callbacks continues to grow with rising tightness.

Keywords: Training, Occupational mobility, Labor demand

JEL Codes: J23, J24, J62

*Azmat: Sciences Po. Behaghel: PSE, INRAE. Hazard: Collegio Carlo Alberto and ESOMAS. Rathelot: Institut Polytechnique de Paris (ENSAE). Sultan: IPP. All errors are our own. Azmat is also affiliated with CEP (LSE), CEPR, CESifo, IZA; Behaghel with Cepremap, IZA, and J-PAL; Rathelot with CREST, CEPR, IZA, J-PAL. The correspondence study used in this paper was registered on the AEA RCT registry in October 2022 under number AEARCTR-0010202. It was approved by the PSE IRB (decisions 2020-023 and 2021-021). We acknowledge funding from the French ministry of labor (DARES) under the Plan d'investissement dans les compétences (PIC). Behaghel, Hazard and Sultan acknowledge funding by EUR grant ANR-17-EURE-0001.

Occupational mismatch in the labor market has become a focal point for researchers and policymakers in recent years (Şahin et al., 2014; Patterson et al., 2016; van Rens and Rathelot, 2017; Modestino et al., 2020; Brunello and Wruuck, 2021). This mismatch arises when job seekers lack the skills that employers require, creating significant frictions that hinder the efficient functioning of the labor market. The implications are substantial, contributing to persistent high unemployment and posing significant challenges to economic growth and stability.

Occupational mismatch can be analyzed from two distinct perspectives: "frictional mismatch," which refers to job seekers not directing their search towards occupations and firms with high hiring potential, and "skills mismatch" which reflects a gap between workers' training or experience and and employers' requirements. Frictional mismatch may arise due to information frictions or a reluctance to transition, driven by factors such as risk aversion, biased decision-making, or unfavorable wages and working conditions in tighter labor markets (Belot et al., 2024). In contrast, skills mismatch stems from shifts in labor demand driven by job creation and destruction, which educational systems struggle to keep pace with. These shifts may result from technological change—leading to, for example, job polarization and declining demand for mid-level skills—or from economy-wide shocks with asymmetric industry impacts, such as the Great Recession (Hershbein and Kahn, 2018) or the COVID-19 pandemic.

Disentangling frictional mismatch caused by information frictions from skills mismatch is challenging. One approach to tackle frictional mismatch has been through public employment services that use caseworkers to inform workers about market imbalances (Schiprowski, 2020). In several countries, recommender systems have been introduced to mitigate these frictions by identifying labor market tightness at a granular level (e.g., specific occupations within commuting zones) and encouraging job seekers to expand their search to tighter occupations. Recent research has shown the potential of such an approach in improving job search assistance.[1] To better understand skills mismatch, studies have evaluated the effectiveness of worker retraining, particularly for unemployed individuals. While retraining programs were traditionally criticized for being costly and ineffective (Heckman et al., 1999; Dar and Gui, 1998), more recent research paints a nuanced picture, suggesting positive medium-term effects following an initial lock-in period (Card et al., 2018).

In this paper, we conduct a large-scale correspondence study in France between 2021 and 2023 to compare the effectiveness of broader occupational search and retraining in

[1] Kircher (2022) provides an overview. Recent papers include Belot et al. (2022, 2023); Altmann et al. (2023); Hensvik et al. (2023); Behaghel et al. (2024).

high-demand labor markets. We manipulate the content of resumes to isolate frictional and skills mismatch. Applications from young workers (aged 21) are sent to job postings in six 'tight' occupations: restaurant employees, hairdressers, carers, bakers, auto-body technicians, and plumbers.[2] Occupations were selected based on their high vacancy volumes (to ensure sufficient sample size), high levels of tightness (to make them relevant target occupations), and regional variation in tightness (to examine its role). For each occupation, we design four candidate profiles, which are then randomly assigned across job postings. The benchmark profile (henceforth, the *incumbent*) has both initial training and experience in the advertised position. A second profile has initial training in a neighboring, related, occupation and applies to the target position without retraining (henceforth, the *untrained mover*). The third and fourth profiles share the untrained mover's initial training but have completed either short (a few days) or long (a few months) retraining in the target occupation (henceforth, the *short-retraining mover* and the *long-retraining mover*, respectively). Firms' callback rates serve as our measure of their preferences for these different profiles. Over 5,000 resumes were sent in total.

Overall, the experiment shows that there is a significant disparity in callback rates among the four types of candidates. As expected, the incumbent candidate receives the highest callback rate, closely followed by the long-retraining mover, with rates of 56% and 46%, respectively. In contrast, the untrained mover and the short-retraining mover receive significantly lower callback rates, both at 30%, with no statistically significant difference between them. It is worth noting the high callback rates across all profiles (even among the untrained movers), which confirms the strong labor demand in the six occupations, consistent with our selection criteria.

Across occupations, we find a great deal of consistency in the main patterns of callback rates, particularly for those undergoing long retraining. We also, however, identify interesting heterogeneity. In three occupations (auto-body technicians, plumbers, and hairdressers), untrained movers receive lower callback rates, while long-retraining results in callback rates similar to incumbents, suggesting that overcoming search frictions alone is insufficient and that retraining interventions are particularly effective. In contrast, two occupations (carers and bakers) show significant gains from retraining but with untrained movers also experiencing relatively high callback rates. This suggests that occupational mobility without retraining may be easier in these occupations. Only

[2]While occupational mismatch may affect all groups of workers, its relevance and the need to design appropriate policies to tackle it are particularly high for youth, especially those with no or lower degrees. Youth unemployment is as high as 10.9% on average in OECD countries (https://www.oecd.org/en/data/indicators/youth-unemployment-rate.html.

one occupation (restaurant employees) exhibits minimal gains from retraining.

Whether government-sponsored retraining is a justified response to skills mismatch in tight labor markets remains unclear. There are two conflicting ways in which labor market tightness may impact the return to training. On the one hand, as conventional wisdom suggests, returns to training are likely to be higher in occupations where skills are in high demand. In markets with low labor demand, whether due to firms' inability to expand or because productivity is so low that hiring trained workers would not be profitable, the impact of training is expected to be negligible. On the other hand, if labor demand is exceptionally high, retraining subsidized by public employment services may simply displace the training that firms would otherwise provide to untrained candidates after hiring them. The high callback rates for untrained movers (around 30%, on average) suggests that firms in tight labor markets are willing to hire unqualified candidates. This may suggest that firms intend to train these workers after hiring them, implying that policies facilitating occupational mobility *without* preemptive retraining could also be effective. This second mechanism suggests that subsidizing retraining might simply become a windfall for firms in particularly tight labor markets.

In the second part of the paper, we formalize these two conflicting effects in a simple partial equilibrium model of the labor market. Firms make the decision to call a worker for an interview, trading off the value of the match against the option value of searching for a more productive candidate. This option value decreases with local tightness. The model shows that the cross-effect of tightness and training depends on the distribution of firms' idiosyncratic productivities around the relevant threshold. Under plausible assumptions, when callback rates remain below 50%, the cross-effect is positive suggesting that the impact of retraining increases with tightness.

We bring the model to the data, taking advantage of the geographical variation in tightness within the different occupations.[3] For all occupations, with the exception of one (restaurant employees), we find that the impact of retraining on callback rates increases with tightness. These results provide evidence that retraining programs have not reached the point where they would be pure windfalls for firms. Furthermore, the fact that returns to training remain positive even in less tight regions and occupations implies that, in the set of occupations we chose, training is productive.

The first contribution of our paper is that it compares the impact of two alternative

[3]For this exercise, we deliberately exploit geographical variation rather than occupational variation in tightness. The reason is that we believe that occupations with different tightness levels likely differ in other confounding dimensions, making it difficult to identify the effect of tightness.

active labor market policies aimed at reducing occupational mismatch—job search recommendations and retraining programs—within a single, coherent setting. This places our study at the intersection of two key strands of literature: the literature on skills mismatch[4], and the literature on active labor market policies (as reviewed in particular by Card et al. (2018)). Our study offers a within-study comparison, which, to the best of our knowledge, is the first paper to do so. An important caveat, common to all correspondence studies, is that our outcomes are limited to callback rates, and we cannot assess impacts on actual employment or conduct a cost-effectiveness analysis without assumptions about how callbacks translate into hires. Nevertheless, callback rates are a relevant measure, as they represent a critical first step toward securing an interview and, ultimately, employment.[5]

Our second contribution is to isolate the labor-demand effect in occupational mismatch. Most evaluations of active labor market policies encompass the combined effect of the job seeker's uptake behavior and the firm's response. As the uptake of training programs, or the use of recommender systems is typically low, the reduced form effect of a typical program evaluation combines the supply and demand responses for a limited, endogenous group of complying job seekers. By controlling the content of resumes sent to firms, we can isolate firms' responses, while controlling the profiles of job seekers to ensure representativeness.

Our third contribution relates to the "how" and "when" of training programs. Literature reviews such as Carranza and McKenzie (2024) have underscored the variety of training programs and the need to provide policymakers with guidance on which program to use under which circumstances. We provide some first insights on this broad question by showing that retraining facilitates occupational transitions and does not only have a windfall effect, even when the target occupation is tight. Additionally, our results provide a clear warning against short retraining that does not seem to improve the job seekers' prospects.

Section 1 presents the context of the experiment. Section 2 presents the protocol of the

[4]This also relates to research on local imbalances between labor supply and demand, which can persist over time in imperfect labor markets, leading to significant consequences such as high unemployment rates or declines in productivity (Şahin et al., 2014; Herz and van Rens, 2020; Guvenen et al., 2020; van Rens and Rathelot, 2017). Skills imbalances can also interact with geographical imbalances when labor mobility is imperfect. Marinescu and Rathelot (2018) show that American job seekers disproportionately apply for jobs near their homes, while Manning and Petrongolo (2017) also show that labor markets in England are highly localized.

[5]See Neumark et al. (1996); Bertrand and Mullainathan (2004); Bertrand and Duflo (2017) for correspondence studies used to identify hiring discrimination. In a related context, Cahuc et al. (2021) use a correspondence study to show that certified training is only effective in areas with very low unemployment rates, specifically for young individuals who have not completed their secondary education.

correspondence study. Section 3 shows the main results on callback rates. Section 4 analyzes the role of tightness from a theoretical and empirical perspective. Section 5 concludes.

1 Institutional context

Our correspondence study aims to measure the effectiveness of retraining on occupational mobility in high demand labor markets in France. For the purpose of the study, all candidates have completed, as part of their initial education, a standard two-year vocational track that they follow after completing middle school. We introduce four types of candidates, including the "incumbent," who has both initial training and experience in the posted occupation, and the "untrained mover," who has initial training in a neighboring, less demanded, occupation. In addition, we introduce the "long-training mover" and the "short-training mover," who have undertaken professional training in a the posted occupation after a few years of professional experience. In order to situate these candidates in the working population in France, this section provides a brief overview of the educational and adult professional training systems in France.

1.1 Initial education in France

In France, education is compulsory between the ages of 6 and 16. After five years of primary school, students enroll in a four-year middle school. Tracking mostly starts in high school. There, students can either follow a "general", a "technological", or a "professional" track. The general track is purely academic, the professional track is purely vocational, and the technological track is a combination of both. After three years of high school, students in these three tracks can take the Baccalauréat exam, and, if successful, enter higher education. Students in the professional track, however, can also stop after a two-year training and take the "Certificat d'aptitude professionnelle" (CAP), a vocational degree that leads to jobs at the first level of qualification in about 200 different occupations.[6] The two-year CAP training program can combine classroom instruction with practical, in-firm experience through the apprenticeship system. The prevalence of apprenticeships varies across occupations. To accurately reflect the variation across occupations, candidates in some of our studied occupations were apprentices, while in others they were not

[6] After CAP, students can pursue their studies to take the Baccalauréat (in the professional track), but in our design, none of our candidates take this track.

Our main candidates of interest were born in 2000, and completed their initial education with a CAP in 2017.[7] Since they do not pursue their studies until the Baccalauréat, they ranks among the bottom quartile of their cohort. However, their professional degree distinguishes them from students leaving school without any degree (beyond middle-school level), and who represent about 10% of a cohort. In France, one to four years after leaving school, the unemployment rate of young workers holding a CAP degree (21.9% in 2022), which is slightly higher than the unemployment rate of workers holding only a Baccalauréat degree (18.3% in 2022). This partly reflects the fact that the two-year vocational track is aimed at providing the worker with skills that make him or her readily operational.[8] There is, however, significant variation in the employment prospects of CAP graduates, depending on their occupation of specialization, especially in services where across eight families of occupation, employment rate 6 months after leaving school vary between 13% (in administration, communication and information) and 43% (in transportation, handling, warehousing).[9]

In summary, the population within our study has achieved the lowest vocational degree. They have a significant advantage compared to those leaving school with no or a middle school diploma but still have significant risks of unemployment. Moreover, their employment prospects vary by occupation and sector. Below, we now consider the adult training opportunities available to them.

1.2 Adult professional training

The adult professional training system is a vast sector with many players. It has as many as 75,000 public and private training providers ("organismes de formation"). Training can also by provided in-house by larger firms with specialized HR staff, and within the schooling system. Training is funded by employers (with minimum level mandated by law), but also by the French public employment agencies and by Régions (the fifteen local entities in which France is divided).

The system is partly segmented since some training providers focus on unemployed job seekers, while other mostly intervene within firms to train employed workers. An

[7] In further analysis and tests of robustness, we vary age and experience. See section 3 for more details.

[8] By comparison, one to four years after leaving school, 40.8% of high-school dropouts are unemployed; they are 11.1% among workers with short higher-education training, and 7.2% with long higher-education training. The average is 14.5% (https://www.education.gouv.fr/reperes-et-references-statistiques-2023-378608, Figure 1 page 288).

[9] See (https://www.education.gouv.fr/reperes-et-references-statistiques-2023-378608, Table 4 page 281). There is also a large gap between graduates who studied in a classroom setting and those who went through the apprenticeship sytem.

important distinction is whether the training leads to a national degree or certification ("formations diplômantes, certifiantes et qualifiantes"). This is typically correlated with the duration of the training. In our study, movers differ in the extent to which they retrain, leading to different types of certification. Among the short-retraining movers, candidates obtained certifying trainings depending on the targeted occupations and characters. Certifying training programs are short (lasting around one week), career-oriented courses primarily designed for individuals already in the workforce. They lead to a certification recognized by professional sectors and registered in the *Répertoire National des Certifications Professionnelles* (RNCP). Trainings undertaken by long-retraining movers lead to a CAP or a *Titre professionnel* (the same level of diploma) obtained in less than a year (usually around 9 months) and include a short internship in a company.

2 Correspondence study design

2.1 Target and source occupations

We study occupational mobility toward "target" occupations in high demand (i.e., "tight" occupations, where few candidates have the required experience or initial training), starting from less tight "source" occupations.

Selection of target occupations The selection of target occupations is based on a list of high-tightness occupations in France. The tightness of the labor market is measured by a composite indicator developed by the French Ministry of Labor that takes into account three dimensions: the hiring difficulties expected by employers, the ratio of job vacancies to the number of job seekers, and the ease with which job seekers can find employment.[10] We exclude certain occupations: those that require high or medium levels of qualifications; with a strong employment-training link; for which there are no appropriate medium or short-duration training options;[11] not experiencing national-level tightness;[12] with a volume of job vacancies too low to create a sample size sufficient

[10] Every year, the ministry publishes the top 30 high-tightness occupations and provides indicators at the department levels (https://dares.travail-emploi.gouv.fr/publication/les-tensions-sur-le-marche-du-travail-en-2022).

[11] This is verified through a search on the "La bonne formation" website.

[12] The measures of required qualification level, tightness, and employment-training link are from the DARES work (see tightness on the labor market in 2019 (DARES Results 2020-032)). The sectors "Communication, Media, and Multimedia" and "Entertainment" are excluded due to their low volume of job vacancies and low number of high-tightness occupations.

for statistical analysis[13].

Matching between target and source occupations For each targeted occupation in the study, a "similar" occupation was identified that shares common skills sought by employers with the targeted occupation, but is less tight. The selection of these source occupations involves the following steps:

First, we use a measure of distance between occupations that combines information on skills from Pôle emploi's "fiches ROME" (files describing each occupation in details) with observed employment-to-employment transitions in the DADS (a database from social security data, see appendix)

Next, we exclude related occupations with high tightness since redirecting job seekers from these occupations to target occupations would locally reduce a candidate shortage problem while aggravating it elsewhere, making such transitions less policy relevant.

Table 1 summarizes the selected occupations.

Table 1: Pairs of targeted occupations and neighbouring ones (French denomination and ROME code)

Targeted occupation	Neighbour
Restaurant employees (G1603)	Commercial employee with multiple specialties (D1507)
Hairdressers (D1202)	Cleaning and sanitation worker (K2204)
Carers (J1501)	Cleaning and sanitation worker (K2204)
Bakers (D1102)	Shelf stocking and self-service (D1507)
Auto body technicians (I1606)	Electronic assembly and wiring (H2605)
Plumbers (F1603)	Landscaping and maintenance of green spaces (A1203)

2.2 Resume design

2.2.1 Training of Candidates

We send out several fictitious resumes to vacancy job postings on *Pôle emploi*'s website, the national employment agency, in which we randomly vary the experience and the

[13] Based on job offer data covering the period from January 2019 to the end of 2020, we constructed a ratio that compares the average monthly number of job vacancies between January 2019 and February 2020 to the average monthly number of job vacancies between September and November 2020. Occupations with insufficient job offer volumes, i.e., below the third quartile of this ratio, were excluded.

amount of training, while keeping other characteristics comparable. For each occupation, we design fictitious resumes. We randomly vary the education and training block to create the four profiles of interest. The resumes include the following information:

Education of Incumbent The candidate holds education and experience (four years) in a target occupation. The job seeker holds a qualification corresponding to the classical education for this occupation. This is a vocational certificate (CAP) in the target occupation.

Education and Training of Movers These candidates hold classic education and experience in a neighboring source occupation. The job seeker holds a qualification corresponding to the classical education for this occupation. To account for the retraining, movers are divided into three branches:

- **Untrained mover** This job seeker has a few years of experience in the source occupation, and applies to vacancies in the target occupation without additional vocational training.
- **Short-training mover** This job seeker is initially trained in the source occupation but undertakes a short vocational training in the target occupation.
- **Long-training mover** This job seeker is initially trained in the source occupation but undertakes a long vocational training in the target occupation.

2.2.2 Other Credentials

Four resumes are sent to each job posting. To avoid detection, we vary the credentials and the layout of these four resumes, thus generating four "characters". To avoid confounding, we cross-randomize these four "characters" with the four training and education profiles of interest, yielding 4×4 resumes in each occupation. When applying to a given job posting, we further randomize the order in which the resumes are sent.

A character is characterized by an identity (first name and last name) evoking a geographical origin, a location of his education and professional experiences, a CV "format" (errors, presentation, names of sections, etc.) and specific hobbies, and finally, a cover letter.

Each resume presents the complete identity of the candidate (first name, last name, date of birth/age, postal address, phone and email address). For two characters, the first part

presents the candidate and his motivations for the job sought in a quick manner. For the other two characters, this information is also present but presented in a "Miscellaneous" section with hobbies or in a header. Professional experience, education, and hobbies are the subject of separate sections presented in a different order depending on the character. All profiles were constructed from an initial training located in the candidate's region of origin.

Age of the candidates Candidates in the different profiles are all 21 years old.[14].

***Soft skills* and other personal information** All characters present three *soft skills* related to the targeted occupation and indicate their immediate availability for the position. In addition, all characters specify that they hold a driver's license and own a vehicle.

Candidate's postal address and geographic mobility To increase comparability between job vacancies, we modify the candidate's postal address before sending the application. A postal address is chosen to be near the job offer.[15]

Professional experience The candidates' professional experiences were constructed from experiences declared online by real candidates. The "Indeed" CV database was used to access the declared experiences, and the corresponding experience was manually selected to construct the candidates' resume.[16]

Hobbies The candidates report similar leisure activities, regardless of the desired profession. One of the three hobbies is related to practicing a high-level sport to indirectly signals good physical condition (all tested professions requiring good physical condition). The second aims to indicate an interest in the desired profession. The third hobby is standard and relatively uninformative about the candidate.

[14] In the extended analysis we vary age, see Section 3

[15] By providing an address close to the job location, candidates implicitly signal that they are available for the position. As this criterion of immediate availability/mobility is likely to strongly increase the probability of being called back by an employer. We also added an explicit mention of a recent relocation in 1 CV out of 4.

[16] Established in 2018, "Indeed" is a job search engine that has developed a CV database service. It has been possible to upload and create CVs on this platform.

2.3 Protocol for job vacancies

Identification of job vacancies The main selection criteria for job vacancies relate to the date of publication of the offer (we prioritize recently published offers), the type of contract for the position (fixed-term or permanent) and the search area (France, excluding Corsica).[17] Other criteria are taken into account, mainly to avoid employer detection. In particular, offers from companies included in the candidates' profiles are excluded, as well as offers from a company that has already been tested. Similarly, we exclude offers that come from employment intermediaries (such as temp agencies or recruitment firms). The resulting geographical spread of vacancies having received at least one of our fictitious application is reported in Figure A3.2.

Gathering employer responses A phone number was assigned to each candidate (a candidate being characterized by a profile, an occupation, and a character). This facilitated identifying callbacks from employers.[18] Callback events are almost instantly redirected to an online spreadsheet consulted by the research assistants every evening.[19] To limit inconvenience for genuine employers or candidates, interview proposals are quickly declined.

2.4 Implementation of study

A total of 6,672 applications were sent in response to 1,743 job vacancies (Table 2). The experiment began with three occupations (baker, body repairer, and plumber) and only male candidates. From October 2022, three new occupations were introduced, and female candidates were added for the following occupations: carer (nursing assistant), restaurant employee, and hairdresser. Starting in March 2023, we over-represented the last three occupations to obtain more robust results for female-dominated occupations, as presented by Figure A3.1 in the appendix, in order to obtain more robust results on female occupations.

The job postings to which applications were sent were chosen randomly and reflect the type of offers that are found in these occupations. Their characteristics are detailed

[17] Offers located in Corsica or in the overseas territories are excluded from our search area to limit the risk of our resumes being detected.

[18] These numbers were purchased on the Twilio communication API, which has many advantages, for example, it allows the configuration of candidates' voicemail messages and stores all events related to a phone number (incoming call, voicemail, SMS).

[19] Fake candidates' emails are also redirected and stored on an online spreadsheet.

Table 2: Job postings and number of applications being sent, per occupation

	Nb job postings	Nb of applications being sent
Female-dominated occupations		
Carers	280	826
Hairdressers	280	818
Restaurant employees	289	831
Male-dominated occupations		
Auto body technicians	299	857
Bakers	290	832
Plumbers	288	834
Totals	1 726	4 998

in Appendix Table A3.1. It is interesting to note that a CAP in the target profession is required in half of the offers, which should limit the positive response rates for untrained movers.

3 Main results

3.1 Impact on callback rates

In Table 3, we descriptively summarize the callback rate across profiles. Overall, we find that callback rates are very high (43% of applications receive a positive response), which is consistent with the tightness in these occupations.

As we might expect, incumbent candidates have the highest likelihood of a positive callback (56%). There is, however, a similarly high callback rate to long-retraining mover candidates are called at a high rate (46%). There is a significant difference still, relative the incumbent, suggesting a penalty to changing professional direction. However, we see that through a full retraining, we close a sizable (two-thirds) of the gap in callback. The lowest callback rate, as we might expect, is among the untrained movers (28%). What is striking, however, is that there is no difference in callback rate between these candidates and the short-retraining movers (27%). This suggests that short-term training does not appear to be more effective in convincing an employer of skills (or motivation) for the target occupation.

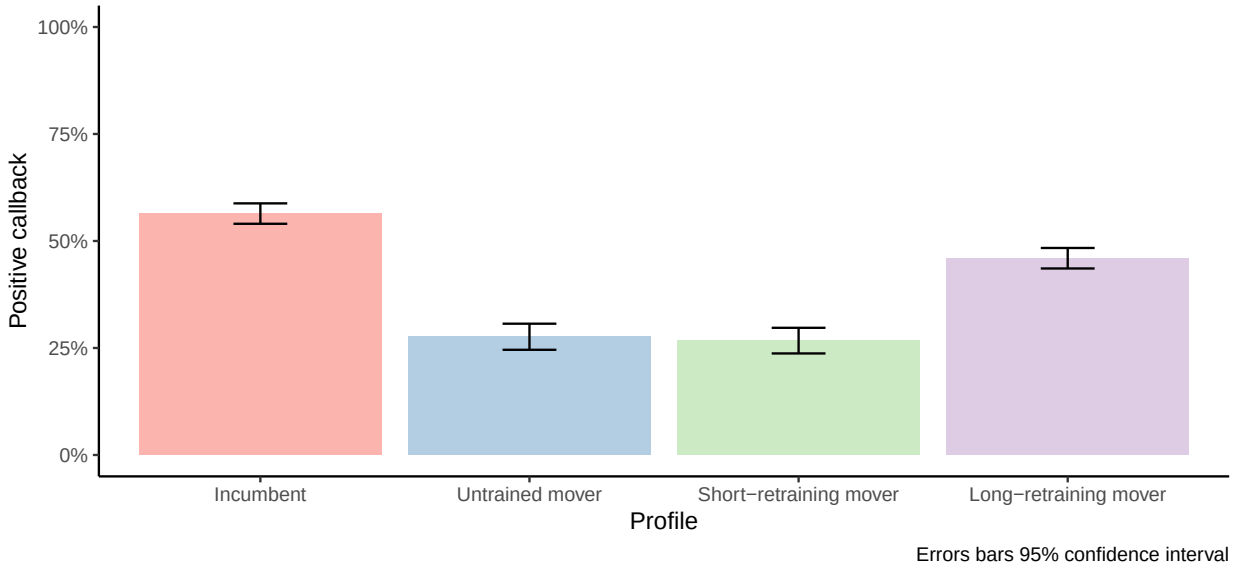
In Table 4, we show the results of the regression analysis. Column 1 computes the gaps across the four different profiles and shows that, relative to the incumbent, callbacks are statistically lower for all other profiles. However, these gaps are much smaller for long-retrained movers, compared with the untrained or short-retrained.

In Column 2, we include detailed controls for the resume identifier, the order in which the resumes were sent, whether the candidate indicates moving to the region, and the distance from candidates address and job located. The results remain robust and the gaps across profiles similar. Similarly, in Column 3, the inclusion of application and vacancy fixed effects does not change the main findings.

Table 3: Positive, negative and non-response callback, per profile

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	1 663	0.56	0.01	0.43
Untrained mover	829	0.28	0.03	0.69
Short-retraining mover	842	0.27	0.03	0.70
Long-retraining mover	1 664	0.46	0.01	0.53
Totals	4 998	0.43	0.02	0.55

Figure 1: Positive callback rate, by profile



Notes: This graph presents the positive callback rate as a percentage of the total applications made by profile, across all occupations. 60% of employers respond positively to the control group A, as well as to the retraining identities with long-term training. There is no difference in callback rates between retraining profiles without training and those with short-term training.

Source:

3.2 Differences across occupations

Figure A3.3 and Tables A3.2-A3.7 highlight some interesting variation across occupations. However, overall, there is a great deal of consistency in the main patterns.

Table 4: Effect of training on probability of callback

	Positive callback		
	OLS	+ controls	+ FEs
	(1)	(2)	(3)
Incumbent	0.5640***	0.7620***	
	(0.0122)	(0.0297)	
Untrained mover	-0.2878***	-0.2657***	-0.2772***
	(0.0197)	(0.0218)	(0.0212)
Short-retraining mover	-0.2968***	-0.2746***	-0.3006***
	(0.0195)	(0.0215)	(0.0203)
Long-retraining mover	-0.1043***	-0.0898***	-0.0972***
	(0.0172)	(0.0173)	(0.0144)
Controls		✓	✓
Fit statistics			
Observations	4,998	4,998	4,998
R^2	0.05974	0.07476	0.70521
Within R^2			0.15997
Adjusted R^2	0.05918	0.07253	0.44663
Within Adjusted R^2			0.15618
Fixed-effects			
Application date			✓
Vacancy			✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Clustered (Application date-Vacancy) standard-errors in parentheses
Notes: Column (1) shows the results of an OLS specification. Column (2) includes control variables: CV id, the order in which the CVs were sent, the fact that the candidate clearly indicates that he/she is moving in the region, the fact that he/she graduated from a CFA, and the time between the candidate's address and the job location. Column (3) includes application and vacancy fixed-effects.

In all occupations, with the exception of restaurant employees, callback rates of the incumbent candidate are above 50%, a strong indication of tightness.[20] All other occupations display similar patterns, with small returns to short retraining (compared to the untrained mover) and large, significant returns to long training. Carers and bakers differ from auto-body technicians, hairdressers and plumbers in that the callback rates of the untrained mover are somewhat larger and the gap with the long-retraining mover somewhat smaller, suggesting that occupational mobility without retraining is easier in these two occupations.

To sum up, it is striking that, with only one exception, the U-shaped pattern in Figure 3 is shared by five occupations out of six, despite large differences in gender composition and industry. This seems to suggest that the results may have some external validity among tight, middle-skilled occupation.

Figure 2: Callback rates by profile and occupation



Notes:

Source:

[20] While still high, the callback rate of incumbent restaurant employees is 38%. This occupation also differs from by small, insignificant returns to retraining: incumbent and movers, whether retrained or not, have similar callback rates. We conjecture that this reflects specific features of this occupation whose tightness may be more related to hard working conditions and low pay than to skills shortage.

3.3 Robustness and further results

Variation of experience We introduce two other profiles to ensure that the results are robust to different levels of experience. First, candidate with a profile similar to the incumbent but born a year later (i.e., three years of experience, excluding initial training). This profile allows us to isolate the effect of an additional year of professional experience that an incumbent would have relative to a mover candidate undergoing retraining. Second, candidate with a profile similar to the incumbent but not having specific experience in the profession. This profile allows us to isolate the pure effect of professional experience.

The results are presented in Table 5. Overall, we find that these profiles have a lower callback relative to incumbents. However, while the additional year of experience has only a small impact on callback (3.5% lower than the incumbent), having no experience does decrease callback (19% lower callback). The comparison between incumbents with four vs. three years of experience shows that about one third of the gap between the incumbents and the long-retraining movers and can be explained by the additional year of work experience (due to the additional year of training of the long-retraining mover).

Survival analysis As an alternative measure of positive callback, we conduct a duration analysis by profile. In Figure 3, we use the Kaplan–Meier estimator to show the callback over the first 31 days since application.

We find that the incumbent and long-retraining mover candidates are recalled the fastest. The difference between the success rate of these applications compared to the untrained and short-retraining profiles are confirmed. Moreover, the incumbent candidates are preferred over the long-retraining mover, with a stable gap. Similarly, the large disadvantage of the other profiles persists over time.

4 Tightness and returns to training

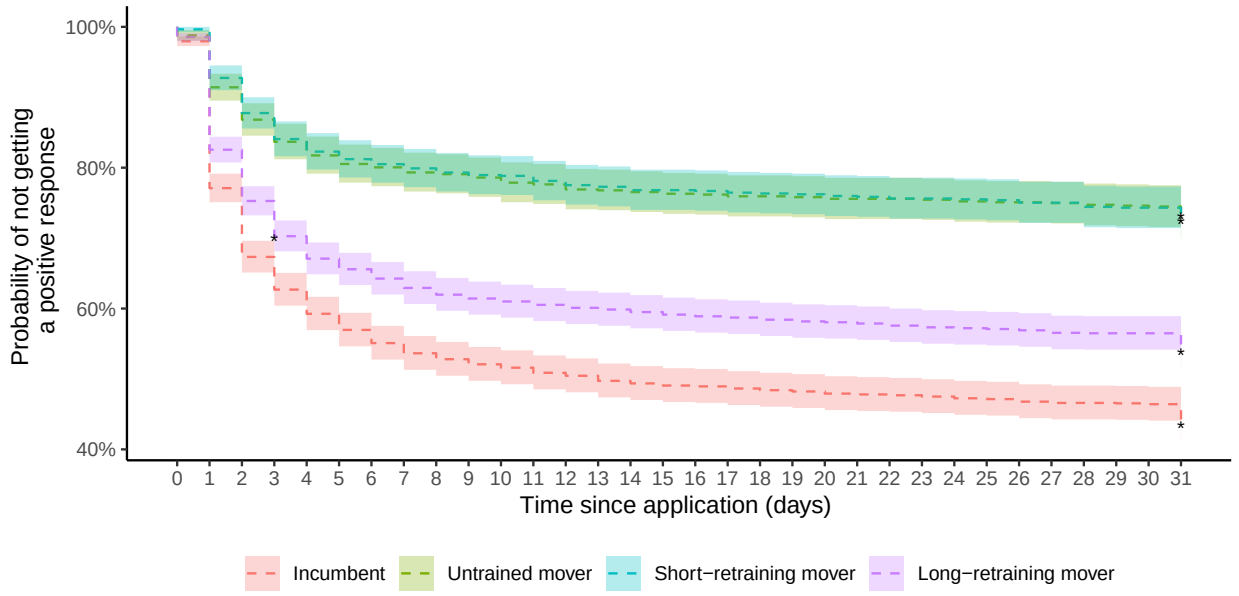
The results presented so far show large returns to retraining workers who change occupation, if the training is sufficiently long. These large effects are found in the context of tight occupations, as evidenced by the very high callback rates of incumbent workers in five of the six occupations. In this section, we analyze how variation in labor market tightness affects the return to retraining, both from a theoretical and empirical perspective.

Table 5: Effect of training on probability of callback

	Positive callback		
	OLS	+ controls	+ FEs
	(1)	(2)	(3)
Incumbent	0.5640***	0.7604***	
	(0.0122)	(0.0263)	
Incumbent - 3 years of experience	-0.0348*	-0.0356	-0.0293
	(0.0211)	(0.0226)	(0.0185)
Incumbent - no experience	-0.1940***	-0.1842***	-0.1788***
	(0.0206)	(0.0223)	(0.0182)
Long-retraining mover	-0.1043***	-0.0888***	-0.0979***
	(0.0172)	(0.0172)	(0.0135)
Short-retraining mover	-0.2968***	-0.2735***	-0.2863***
	(0.0195)	(0.0214)	(0.0189)
Untrained mover	-0.2878***	-0.2641***	-0.2802***
	(0.0197)	(0.0217)	(0.0197)
Controls		✓	✓
Fit statistics			
Observations	6,672	6,672	6,672
R^2	0.05136	0.06840	0.65571
Within R^2			0.12260
Adjusted R^2	0.05065	0.06644	0.46760
Within Adjusted R^2			0.11975
Fixed-effects			
Application date			✓
Vacancy			✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Clustered (Application date-Vacancy) standard-errors in parentheses
Notes: Column (1) shows the results of an OLS specification. Column (2) includes control variables: CV id, the order in which the CVs were sent, the fact that the candidate clearly indicates that he/she is moving in the region, the fact that he/she graduated from a CFA, and the time between the candidate's address and the job location. Column (3) includes application and vacancy fixed-effects.

Figure 3: Survival analysis, by profile



4.1 Tightness and returns to retraining in a partial equilibrium model

We consider a matching model where workers and employers search for each others on a labor market with frictions. Employers post jobs, workers send applications to these jobs, and employers screen these applications and decide which applicants to call back. In what follows, we focus on employers' decisions to call back candidates, as a function of candidates' perceived productivity, and the tightness in the market of the job they posted. To keep things simple, we assume that the productivity y_{ij} of applicant i in the job j posted by the employer has an additive structure:

$$y_{ij} = y_i + \eta_j$$

where y_i is the productivity of applicant i as assessed by the employer, considering the application file of the worker (e.g., resume credentials, education, experience, training), and η_j is a job-employer specific component.

We assume that, for a given job, employers decide on a threshold $y^*(\theta_l)$, which depends on the tightness θ_l in the local labour market l. If the perceived productivity of the match y_{ij} is higher than $y^*(\theta_l)$, applicant i will be called back. Formally, applicant i is called back if and only if $y_{ij} > y^*(\theta_l)$. The probability of callback from the point of view of applicants, integrating over the distribution of η_j is thus $p_{il} = F[y_i - y^*(\theta_l)]$, where $F(.)$ is the cumulative density function of $-\eta_j$.

We assume that what retraining does is improving the perceived productivity y_i of applicants, thereby increasing the probability to be called back p_{il}. The question we ask is: how does the impact of retraining depend on the labour market tightness? In other terms, how does the derivative of p_{il} depend on θ_l? To answer this question we have to make an assumption about the derivative of the productivity threshold y^* with respect to θ_l. Intuitively, firms facing a higher tightness may be tempted to lower the productivity threshold y^* and consider less skilled candidates. Indeed, one can show within a simple partial equilibrium search and matching model that $\frac{\partial y^*}{\partial \theta_l} < 0$ (see Appendix A3.1).

How the impact of a marginal unit of training depends on tightness is dictated by the following cross-derivative:

$$\frac{\partial^2 p_{il}}{\partial y_i \partial \theta_l} = -\frac{\partial y^*}{\partial \theta_l} f'[y_i - y^*(\theta_l)]$$

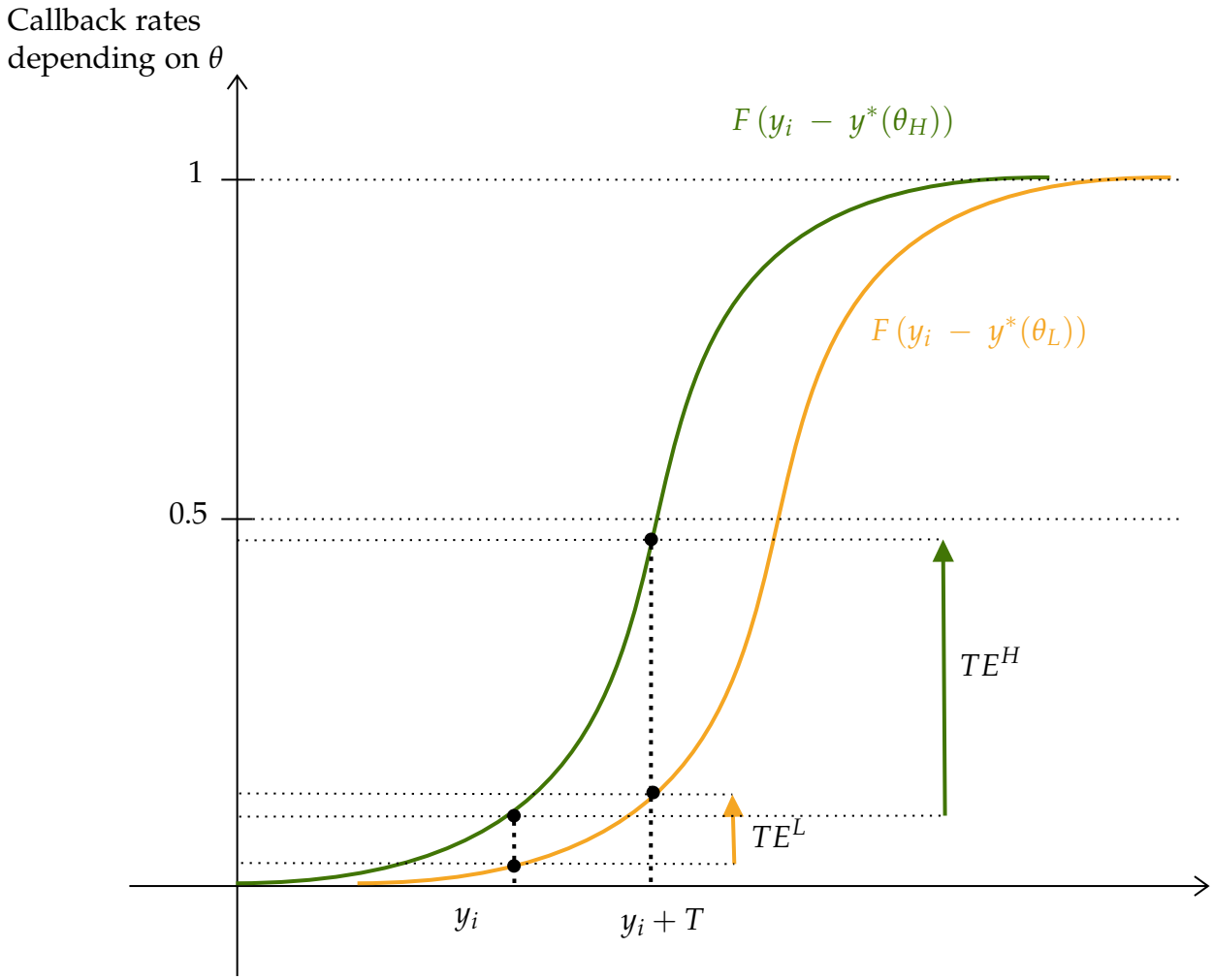
where $f(.)$ is the probability density function of $-\eta_j$. Sticking to the case in which $\frac{\partial y^*}{\partial \theta_l} < 0$ (employers lower the threshold in tighter markets), the sign of the cross-derivative thus depends on the shape of f. Assume that f is unimodal, increasing and then decreasing. Then, for a given worker i, $f'[y_i - y^*(\theta_l)]$ is positive when tightness θ_l is low (as it implies a low value of $y_i - y^*(\theta_l)$) and negative when tightness is high.

This result illustrates the debate around targeting more or less tight markets for retraining. On the one hand, retraining may work better in contexts in which employers are eager to hire workers. On the other hand, if employers already have a bar so low that they would hire anyone, training should have a relatively low impact. Both intuitions are valid; it simply depends on where we are located on the $y_i - y^*(\theta_l)$ line. Figure 4 illustrates this reasoning graphically by showing how the impact of training may vary as a function of labour-market tightness.

4.2 Results

We bring the model to the data using one important feature of our design, the selection of occupations with large local variation in tightness. Figure 5 illustrates that variation. Tightness is measured by the ratio of the number of vacancies over the number of job seekers (V/U) in each occupation. In many cases, this ratio varies by a factor of three in adjacent jurisdictions (*départements*).

Figure 4: Illustration of how the impact of training may vary as a function of labour-market tightness



Notes: The picture represents the callback rates predicted by our model in tight (green curve) and slack (orange curve) markets, depending on the value of the idiosyncratic individual productivity component y_i and the additional productivity brought by training T. The callback rates in tight markets are predicted to be higher due to the negative effect of tightness on the productivity threshold y^* used by employers to determine whether an applicant is productive enough to be hired. The green and orange arrows represent the treatment effect of providing training (with additional productivity T) on callback rates in tight and slack markets, as predicted by our model.

Figure 5: Tightness (V/U) by local labor market

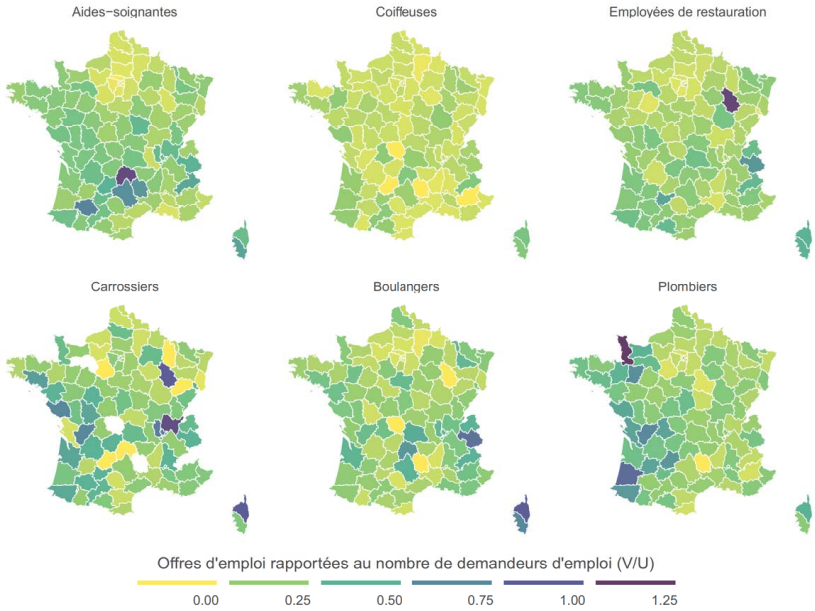


Figure 6 plots non-parametric estimates of the relationship between log-tightness and callback rates, by profile. Given their indistinguishable callback rates, we pool untrained and short-training movers to increase statistical precision. For the same reason, we add one-year younger profiles to the group of incumbent candidates.[21] Reassuringly, callback rates are increasing in log-tightness for the three profiles. The return to long-retraining (compared to the untrained mover) is positive at all tightness level, but tends to increase with tightness. The graphical evidence thus suggests a positive cross-effect of training and tightness on callback rates. Appendix Table A3.8 provides regression results by occupation. Not suprisingly perhaps, restaurant employees again appear as an outlier, with little direct and cross-effect of tightness. In all other occupations, though, the point estimates suggest positive cross-effects of retraining (long-training movers) or

[21] To net out the effects of observable application and firm characteristics, we follow Cattaneo et al. (2024) who develop a valid way of plotting (through "binscatters") the non-parametric relationship between two variables, net of linear adjustments. In our case, the callback rates are implicitly modeled as generated by a partially linear (hence semi-parametric) model where its relationship with the log-tightness is left unrestricted, while its dependence on observable application and firm characteristics is modeled as linear.

initial training (incumbents) and tightness. To gain power, we pool occupations. For transparency, column 1 pools all occupations, including restaurant employees. While the cross-effect point estimates are positive, they are not or marginally significant. In our preferred specification (column 5), we exclude restaurant employees who seem to obey a different logic. We find meaningful and significant cross-effect: a twofold increase in tightness (V/U) increases callback rates by about 6%. Put differently, the effect of tightness increases almost twofold ($= 0.0602/(0.0688 + 0.0602)$) with long retraining.

Overall, our results show that the high level of tightness in the occupations studied helps explain the particularly high callback rates. Importantly, however, despite already high callback probabilities, firms still value the job seeker's retraining. Viewed through the model's lens, this implies that firms have not reached the area in which they would hire almost anyone, so that most job seekers are infra-marginal with regard to training. This provides a rationale for retraining policies in those markets, as a way to increase job finding rates.

Figure 6: Heterogeneity of callback rates along tightness

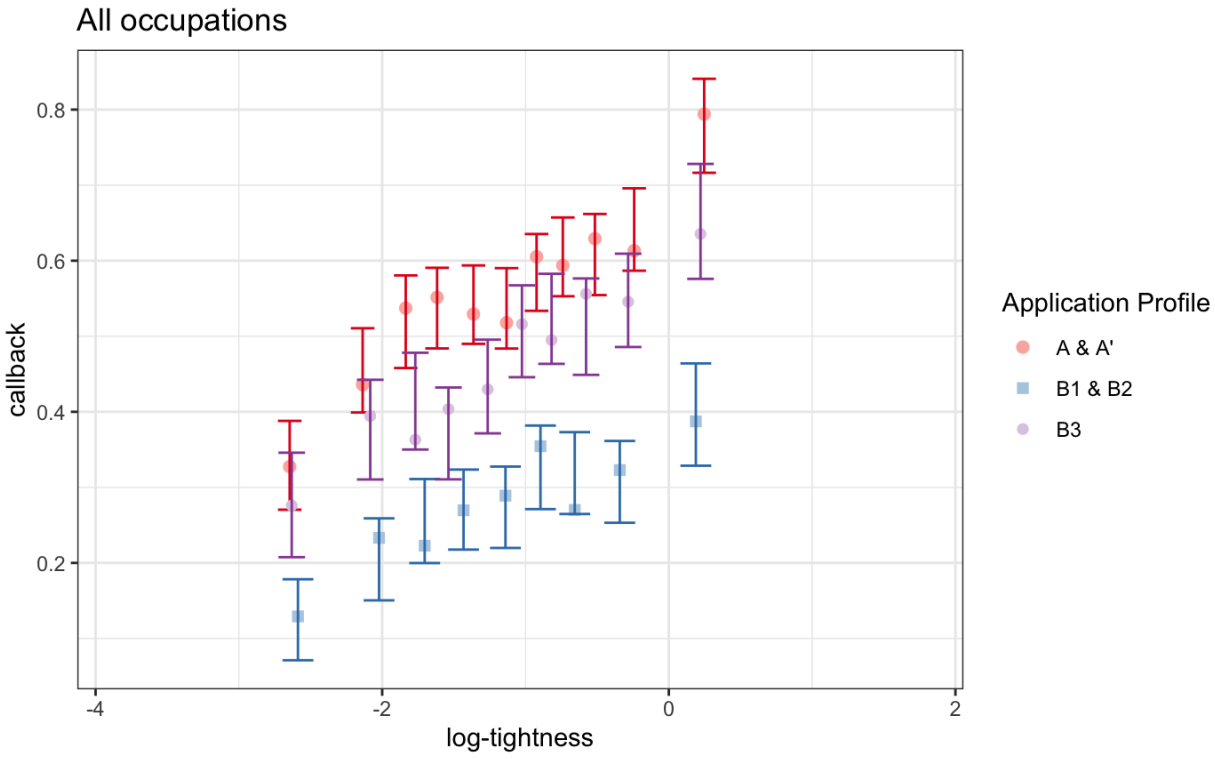


Table 6: Heterogeneity along tightness, by group of occupations

	Positive callback				
	All occupations	Group 1	Group 2	Group 3	Group 4
	(1)	(2)	(3)	(4)	(5)
Log-tightness	0.0941***	0.0546**	0.1326***	0.0557**	0.0688***
	(0.0182)	(0.0259)	(0.0314)	(0.0222)	(0.0204)
Log-tightness x Incumbent (A and A')	0.0417*	0.0744**	-0.0065	0.0904***	0.0590**
	(0.0245)	(0.0357)	(0.0411)	(0.0303)	(0.0274)
Log-tightness x Long retraining mover (B3)	0.0341	0.0683*	-0.0020	0.0823**	0.0602**
	(0.0269)	(0.0384)	(0.0441)	(0.0328)	(0.0297)
Controls	✓	✓	✓	✓	✓
Fit statistics					
Observations	5,625	2,821	2,804	3,763	4,710
R^2	0.24250	0.32568	0.31909	0.26653	0.26991
Within R^2	0.14484	0.13786	0.14263	0.12696	0.15675
Adjusted R^2	0.14540	0.13994	0.13950	0.12207	0.15756
Within Adjusted R^2	0.13764	0.12499	0.12987	0.11696	0.14869
Fixed-effects					
application_date	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Clustered (Application date-Vacancy) standard-errors in parentheses
Controls include the candidate identity, the sending order of the application (compared to others sent to the same employer), the duration of the travel between the applicant reported address and the employer address, whether or not the applicant indicates to have moved recently (along with application date fixed effects). All controls are interacted with the profile category. Occupations of group 1 include auto-body technicians, hairdressers and plumbers. Occupations of group 2 include restaurant employees, carers and bakers. Occupations of group 3 are all occupations but restaurant employees and carers. Occupations of group 4 are all occupations but restaurant employees.

5 Conclusion

In a large correspondence study covering six middle-skilled (tight) occupations, we document firms' labor demand for candidates moving from neighboring occupations, with different amounts of retraining. Occupational mismatch presents a significant challenge to labor markets, characterized by gaps between job seekers' skills and employers' requirements. It is often challenging to identify whether this mismatch stems from job search frictions, or from skills mismatch. Our study provides insights into these channels, focusing on callback rates as a measure of firms' responses to candidate profiles with varying levels of training and experience.

Consistent with being in a tight labor market, callback rates are generally high, with the highest being for the incumbent, who has both initial training and experience in the posted occupation. Callback rates increase, however, meaningfully when the candidate has received a long retraining. The impact of short retraining programs is less clear. While there is some heterogeneity across occupations in their returns, more generally, the callback rate is significantly lower than for long retraining. In many cases, it is not economically or statistically different from being untrained.

While untrained candidates have the lowest callback rates relative to the incumbents and long retrained (and, in some cases, the short retrained), in this context of tight occupations, we find that firms call back candidates without retraining at a significant rate (around 30% on average). This raises the question of whether reorienting job seekers' without providing retraining may also be an effective policy. The effectiveness of government-sponsored retraining in tight labor markets is, therefore, uncertain, as labor market tightness can influence training returns in conflicting ways. We develop a partial equilibrium model to examine how labor market tightness and training interact to influence firms' hiring decisions. Using data on geographical variation in labor market tightness, we show that retraining returns are even larger in tight local markets, suggesting that retraining interventions have not reached the point at which most job seekers are infra-marginal and retraining policies are a windfall to firms.

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A3 Appendix

A3.1 Proofs

Employers first decide whether to post vacancies, paying a cost c each period while the vacancy is open. We adopt a random-search setting, employers have a probability $q(\theta)$ to meet a worker on this labor market of tightness θ—which is taken as an exogenous parameter, as we limit ourselve to a partial equilibrium analysis. When an employer meets a worker, the productivity of the potential match is drawn from a distribution of cdf F, and the realized productivity of the match y is observed by the employer. If y is higher than a reservation value y^*, which depends on the structural parameters of the model, the employer hires the worker. While the match lasts, it produces y, the employer pays the worker an exogenous w. The match breaks with probability δ.

We can write the flow value $r\Pi(y)$ of a job with flow productivity y, and the flow value rV of a vacant position, where r is the discount factor, as

$$\begin{aligned} r\Pi(y) &= y - w - \delta[\Pi(y) - V] \\ rV &= -c + q(\theta)\int_0^\infty \max\{[(\Pi(z) - V), 0\}dF(z) \\ &= -c + q(\theta)\int_{y^*}^\infty [\Pi(z) - V]dF(z) \end{aligned}$$

where y^* denotes the reservation productivity, which is the (flow) productivity level that makes the employer indifferent between continuing to search for a worker (with payoff V) or hiring a worker at productivity level $y = y^*$ — with a present discounted value of $\Pi(y^*)$.[22] Formally:

$$\Pi(y^*) = V.$$

Notice that combining the first equation of the flow profit and the above condition characterizing y^*, we get:

$$\Pi(y) - V = \frac{y - w - rV}{r + \delta}$$

so that the reservation productivity can also be expressed as:

$$y^* = w + rV$$

One can prove that the value of a vacancy V decreases with tightness θ — see Appendix

[22] Since $\Pi(y)$ is strictly increasing in y, and V does not depend on y, there is a unique value of $y*$ satisfying this condition.

Section A3.1 — through a decrease in the likelihood to meet a candidate worker in the future. Hence it reduces the reservation productivity y^*, since the option value of waiting for a (better) candidate is reduced. We thus have that $\frac{dy^*}{d\theta} < 0$ in this partial equilibrium model.

Remark. This dependence of the productivity threshold y^* on the tightness vanishes entirely in general equilibrium. Indeed, once tightness is endogenized through the free entry condition, firms post vacancies up to the point where $V = 0$, and we simply get $y^* = w$.[23]

Deriving and signing $\frac{dy^*}{d\theta} < 0$ in partial equilibrium model (section 4.1) The result relies on the fact that $\frac{\partial V}{\partial \theta} < 0$, which can be shown as follows. Going back to the flow value of a vacancy, we have:

$$
\begin{aligned}
rV &= -c + q(\theta) \int_{y^*}^{\infty} [\Pi(z) - V] dF(z) \\
\Leftrightarrow \quad (r + q(\theta) \cdot [1 - F(y^*)]) \cdot V &= -c + q(\theta) \int_{y^*}^{\infty} \Pi(z) dF(z) \\
&\text{where } \Pi(z) = \frac{z - w - rV}{r + \delta} \\
&= -c - q(\theta) \frac{r}{r+\delta} [1 - F(y^*)] V + q(\theta) \int_{y^*}^{\infty} \frac{z - w}{r + \delta} dF(z) \\
\Leftrightarrow \quad \left(r + q(\theta) \cdot [1 - F(y^*)] \cdot \left(1 + \frac{r}{r+\delta} \right) \right) \cdot V &= -c + q(\theta) \int_{y^*}^{\infty} \frac{z - w}{r + \delta} dF(z)
\end{aligned}
$$

[23] The fact that the threshold y^* is not altered by any variation of tightness in general equilibrium is left unchanged once one introduces fixed costs in vacancy posting. Indeed, it would simply yield a threshold $y^* = w + rK$, where K is the fixed cost to posting a vacancy.

Hence:

$$\frac{\partial V}{\partial \theta} = \Bigg[\underbrace{\left(q'(\theta) \cdot \int_{y^*}^{\infty} \frac{z-w}{r+\delta} dF(z) \right) \cdot \left(r + q(\theta)\left[1 - F(y^*)\right] \cdot \left(1 + \frac{r}{r+\delta} \right) \right)}_{<0} + \underbrace{\left(-c + q(\theta) \int_{y^*}^{\infty} \frac{z-w}{r+\delta} dF(z) \right)}_{>0 \text{ since we assume } rV>0} \cdot \underbrace{\left(q'(\theta)\left[1 - F(y^*)\right] \cdot \left(1 + \frac{r}{r+\delta} \right) \right)}_{<0} \Bigg] \times \underbrace{\left(r + q(\theta) \cdot \left[1 - F(y^*)\right] \cdot \left(1 + \frac{r}{r+\delta} \right) \right)^{-2}}_{>0}$$

$$< 0$$

hence the result that $\frac{\partial V}{\partial \theta} < 0$.

A3 Additional tables and figures

A3.1 Implementation

Figure A3.1: Seasonality

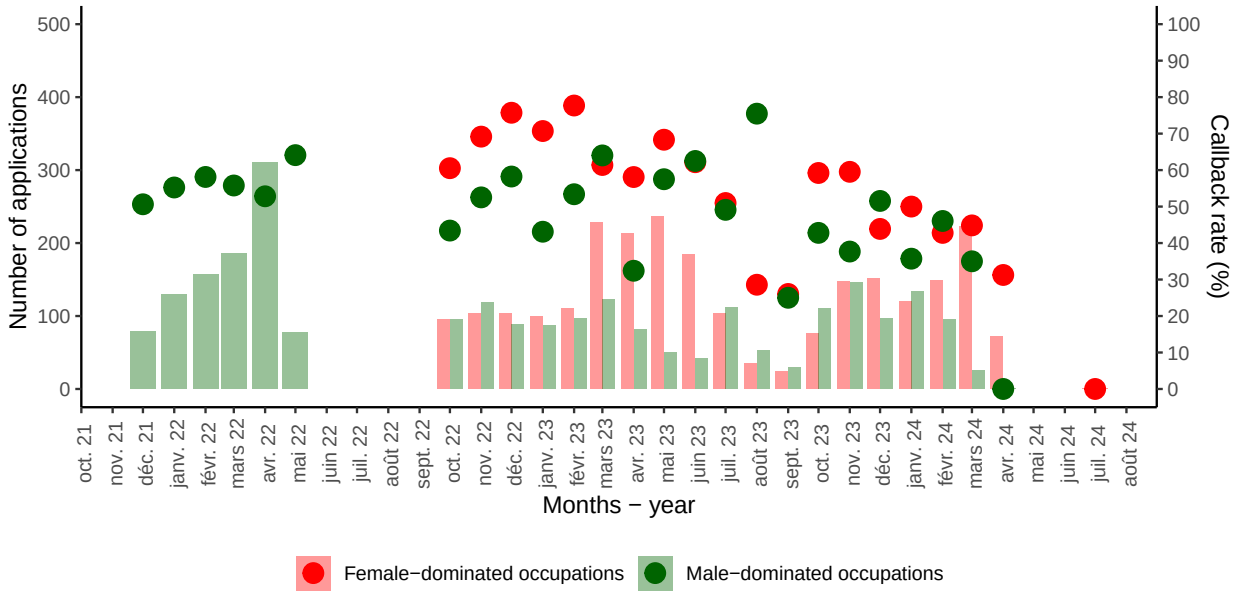
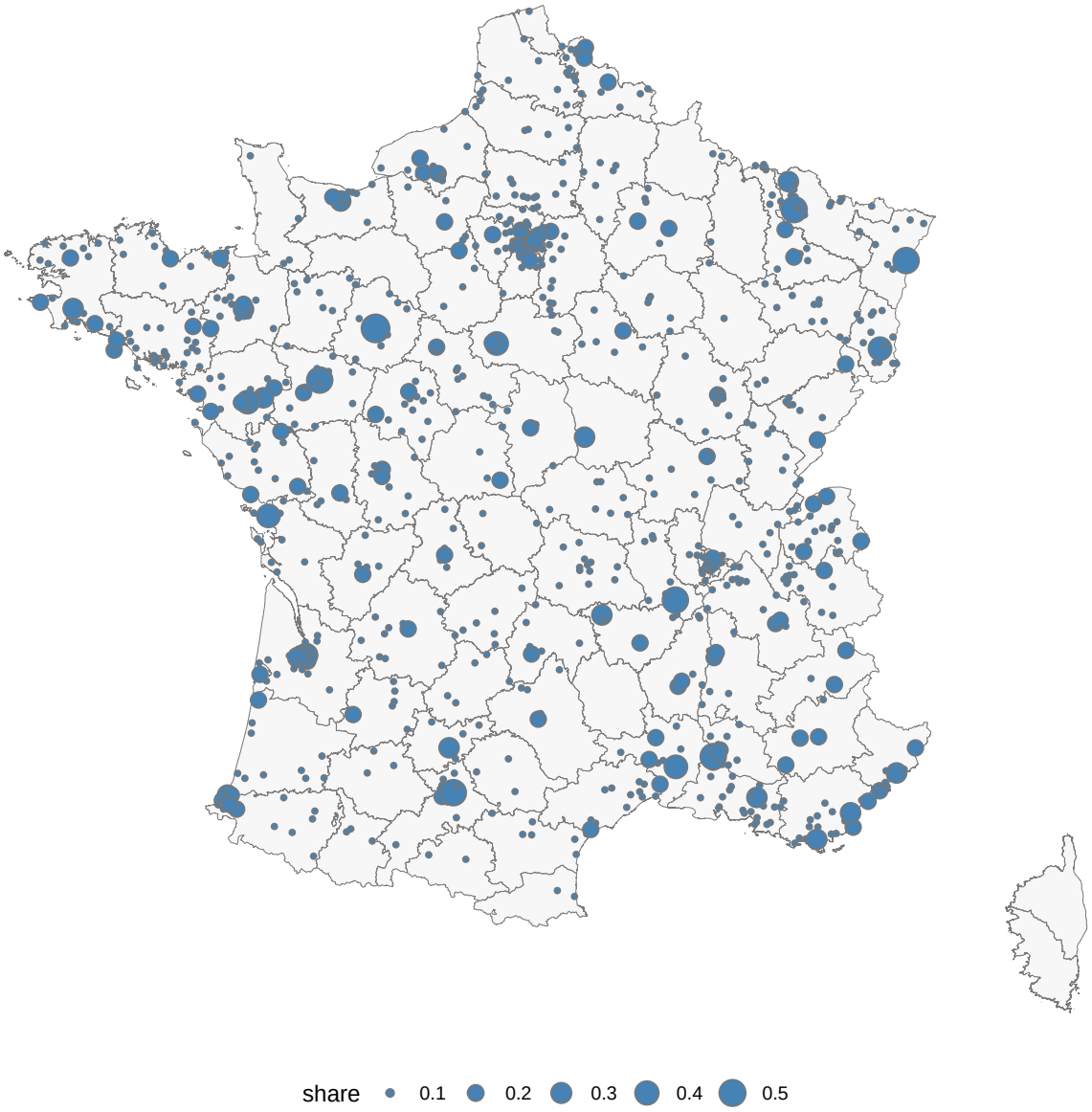


Figure A3.2: Geographical spread of vacancies having received at least one application



Notes: The map shows the number of vacancies to which fictitious applications were sent as a proportion of the total number of vacancies for the 6 occupations combined, by municipality. For ethical reasons and to avoid detection, the proportion of vacancies to which we responded never exceeded 50%. Some municipalities with a very low number of vacancies therefore did not receive any applications. The survey covers the whole of mainland France, with the exception of Corsica.

Source:

A3.2 Descriptive statistics on job postings

Table A3.1: Job vacancies characteristics

	Nb of job vacancies	Proportion
Occupations		
Carers	101	0.12
Hairdressers	102	0.12
Restaurant employees	94	0.11
Auto body technicians	192	0.22
Bakers	194	0.22
Plumbers	191	0.22
CAP required		
No	340	0.39
Yes	418	0.48
Missing information	116	0.13
Experience appreciated		
No	125	0.14
Yes	414	0.47
Missing information	335	0.38
Number of years of experience		
No year of experience	387	0.44
Less than one year	25	0.03
From 1 to 2 years	118	0.14
From 2 to 5 years	206	0.24
More than 5 years	52	0.06
Missing information	86	0.10
Fixed-term contract		
No	610	0.70
Yes	192	0.22
Missing information	72	0.08
Part-time work		
No	742	0.85
Yes	63	0.07
Missing information	69	0.08
Number of hours		
35 hours	353	0.40
Less than 35	63	0.07
More than 35	389	0.45
Missing information	69	0.08
Pre-set hourly wage		
No	196	0.22
Yes	608	0.70
Missing information	70	0.08
All vacancies	874	1.00

A3.3 Additional results

Figure A3.3: Callback rates by profile and occupation



Source:

Table A3.2: Positive, negative and non-response callback, per profile, Carers

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	276	0.73	0.00	0.27
Untrained mover	134	0.53	0.02	0.46
Short-retraining mover	139	0.43	0.01	0.56
Long-retraining mover	277	0.72	0.00	0.28
Totals	826	0.64	0.01	0.35

Table A3.3: Positive, negative and non-response callback, per profile, Hairdressers

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	273	0.59	0.02	0.38
Untrained mover	139	0.14	0.05	0.81
Short-retraining mover	133	0.18	0.04	0.78
Long-retraining mover	273	0.38	0.03	0.59
Totals	818	0.38	0.03	0.59

Table A3.4: Positive, negative and non-response callback, per profile, Restaurant employees

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	273	0.38	0.01	0.62
Untrained mover	140	0.37	0.01	0.62
Short-retraining mover	141	0.29	0.04	0.67
Long-retraining mover	277	0.35	0.01	0.65
Totals	831	0.35	0.01	0.64

Table A3.5: Positive, negative and non-response callback, per profile, Auto body technicians

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	286	0.57	0.01	0.42
Untrained mover	146	0.14	0.05	0.82
Short-retraining mover	141	0.21	0.04	0.76
Long-retraining mover	284	0.41	0.01	0.58
Totals	857	0.38	0.02	0.60

Table A3.6: Positive, negative and non-response callback, per profile, Bakers

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	277	0.57	0.01	0.42
Untrained mover	136	0.30	0.04	0.65
Short-retraining mover	141	0.32	0.01	0.67
Long-retraining mover	278	0.51	0.01	0.48
Totals	832	0.46	0.02	0.52

Table A3.7: Positive, negative and non-response callback, per profile, Plumbers

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	278	0.54	0.01	0.45
Untrained mover	134	0.19	0.04	0.78
Short-retraining mover	147	0.18	0.04	0.78
Long-retraining mover	275	0.40	0.02	0.58
Totals	834	0.37	0.03	0.60

Table A3.8: Heterogeneity along tightness, by occupation

	Positive callback					
	Bakers	Hairdressers	Plumbers	Restaurant Emp.	Auto-body Tech.	Carers
	(1)	(2)	(3)	(4)	(5)	(6)
Log-tightness	0.0660	0.0910	0.0413	0.2127***	0.0500	0.0814
	(0.0640)	(0.0640)	(0.0497)	(0.0530)	(0.0673)	(0.0752)
Log-tightness x Incumbent (A and A')	0.0705	0.0555	0.0788	-0.0257	0.1133	-0.0091
	(0.0856)	(0.0895)	(0.0673)	(0.0748)	(0.0871)	(0.0944)
Log-tightness x Long retraining mover (B3)	0.1072	0.0120	0.0797	-0.1008	0.1275	0.0659
	(0.0877)	(0.0997)	(0.0669)	(0.0818)	(0.0993)	(0.1045)
Controls	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	942	922	961	915	938	947
R^2	0.49364	0.52651	0.53673	0.40344	0.51086	0.39122
Within R^2	0.12744	0.18557	0.16503	0.09643	0.15127	0.12776
Adjusted R^2	0.08544	0.18641	0.15610	0.04842	0.07968	0.08295
Within Adjusted R^2	0.08222	0.14455	0.12225	0.05385	0.10526	0.09026
Fixed-effects						
application_date	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Clustered (Application date-Vacancy) standard-errors in parentheses

Controls include the candidate identity, the sending order of the application (compared to others sent to the same employer), the duration of the travel between the applicant reported address and the employer address, whether or not the applicant indicates to have moved recently (along with application date fixed effects). All controls are interacted with the profile category.