Occupational mobility and retraining: Experimental evidence on firms' hiring preferences

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Abstract

Governments typically address occupational mismatch through two types of interventions: (i) redirection policies, which nudge workers toward tighter labor markets, and (ii) retraining policies, which aim to bridge skill gaps. To assess the effectiveness of these policies in a unique setting, we conducted a large-scale correspondence experiment in France, sending 6,668 fictitious applications across six tight occupations and randomly varying applicants' training and experience. We find that candidates with both initial training and experience in the target occupation received the highest callback rate, followed closely by movers who completed long retraining programs. Short-retraining and untrained movers received half as many callbacks. We also find that the retraining premium increases with the tightness in the local labor market. These results clarify the relative effectiveness of redirection versus retraining policies; we conclude by discussing the conditions under which the costs of these two policy instruments for the government are offset by savings on unemployment benefits.

Keywords: Training, Occupational mobility, Labor demand

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The coexistence of occupations facing high labor demand or low supply alongside occupations facing low demand and high supply 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, Herz and van Rens, 2020, Modestino et al., 2020, Brunello and Wruuck, 2021]. At the macroeconomic level, the implications of such an occupational mismatch are substantial: persistently high unemployment and challenges to economic growth and stability.

Governments have implemented two main types of policies to address imbalances across occupations. First, policies that encourage job seekers to apply to shortage occupations, whether through caseworker intermediation, information campaigns, or the use of recommender systems.[1] These policies are inexpensive but may be ineffective if recruiters are unwilling to hire workers whose skills are tied to other occupations. Second, governments have implemented retraining programs that prepare job seekers for new occupations. These policies are costly, both in terms of training provision and the opportunity costs involved (lock-in effect). The first question we shed light on is: should governments finance costly retraining policies, or rely solely on search-redirection policies?

The answer to this question may depend on how tight the target occupation is. There are two conflicting ways in which labor market tightness may affect employers' demand for (re)trained candidates compared to candidates changing occupations without training. On the one hand, retraining may have low returns in local labor markets[2] with low labor demand, as even retrained workers may not be productive enough to be hired. 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. Our analysis aims to shed light on this second question: how does the trade-off between retraining and search-redirection change with the tightness in the target market?

In this paper, we investigate firms' hiring preferences for workers changing occupations with and without retraining. We conducted a large-scale correspondence study in France, responding to job postings in six occupations. For each occupation, we designed four candidate profiles, which were then randomly assigned across job postings. The benchmark profile (henceforth, the *incumbent*) has both initial training and experience

[1] Recent research has shown the potential of such approaches in improving job search assistance. 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], Bied et al. [2023].

[2] We define local labor markets as 4-digit occupations $\times$ commuting zones.

in the advertised position. A second profile has initial training in a neighboring occupation and applies to the target position without retraining (henceforth, the *untrained mover*).[3] The third and fourth profiles share the untrained mover's initial training and experience 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). We selected occupations characterized by high levels of tightness and significant regional variation in tightness—these criteria allow us to test the impact of retraining conditional on applying in high-tightness occupations, and to document how this impact further varies with regional tightness within those occupations.

We sent 6,668 applications from young workers (aged 21) to 1,743 job postings for restaurant employees, hairdressers, carers, bakers, auto-body technicians, and plumbers in France between 2021 and 2024.[4] We find a significant disparity in callback rates among the four types of candidates. The incumbent candidate receives the highest callback rate (56%), closely followed by the long-retraining mover (46%). The untrained mover and the short-retraining mover receive lower callback rates, both around 27%. Callbacks are high for all profiles (even among untrained movers), which confirms the strong labor demand in the six occupations.

How does the premium associated with retraining change with tightness? To answer this question, we take advantage of geographical variation in tightness within the different occupations.[5] For all occupations, with the exception of one (restaurant employees), we find that the impact of retraining on callback rates increases with tightness. This suggests that, even in these tight occupations, retraining programs have not reached the point at which windfall effects dominate.

Taking stock of our empirical results, we establish that (i) retraining is associated with a clear and substantial premium in the probability of being called back, and (ii) this premium increases with the tightness of the target labor market. To understand the policy trade-off between retraining and search-redirection policies, we leverage this empirical evidence to conduct a cost-benefit analysis of the two policies. We calibrate

[3]Our characterization of neighboring occupations combines task descriptions and observed transitions, as detailed below. To fix ideas, we consider moving from "Cleaning and sanitation worker" to "Carer" or "Hairdresser," or from "Landscaping and maintenance of green spaces" to "Plumber."

[4]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).

[5]For this exercise, we deliberately rely on geographical variation rather than occupational variation in tightness. We believe that occupations with different tightness levels likely differ in other confounding dimensions, making it difficult to identify the effect of tightness.

a simple model in which the benefits of the policies consist of accelerating transitions between unemployment and employment, while the costs include both pedagogical costs (for retraining) and unemployment insurance costs during job search. We find that whether retraining is cost-effective crucially depends on assumptions about its long-term impact on job-finding rates. If the callback premium is limited to the short run, the costs of retraining are not compensated by its benefits. If untrained movers do not catch up and retrained movers continue to work in shortage occupations for several decades, the benefits of retraining may outweigh its costs relative to redirection nudges.

The first contribution of our paper is to isolate the contribution of the demand side to 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 standardizing the content of the résumés submitted to firms, we are able to isolate firms' responses while simultaneously holding constant job seekers' profiles to ensure representativeness. 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.[6] Another paper close to ours is Klaeui et al. [2025]. Using data from a recruitment platform, they control for applicants' characteristics to isolate recruiters' preferences. They find that recruiters strongly favor candidates whose current occupation matches the advertised job, but less so in tighter labor markets. Differently from that paper, we focus on training rather than past occupations, and we rely on experimental variation.

The second contribution of our paper is to compare the impact of two alternative 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 strands of literature: the literature on active labor market policies (as reviewed in particular by Card et al. 2018), and the literature on skills mismatch.[7] Our study is, to the best of our knowledge, the first to offer a within-study

[6]See Neumark et al. [1996], Bertrand and Mullainathan [2004], Bertrand and Duflo [2017] for correspondence studies used to identify hiring discrimination. 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.

[7]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

comparison.[8]

Our third contribution relates to the literature on the effectiveness of training programs for the unemployed. We provide experimental evidence in a literature that mostly relies on non-experimental or quasi-experimental empirical settings [Card et al., 2018]. We also bring evidence about "how" and "when" training programs should be used. 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. In a recent paper, Humlum et al. [2024] use a caseworker-IV design and find large impacts of classroom retraining. They show that these impacts are due to skill acquisition rather than threat effects and that they are stronger on workers pushed away from occupations exposed to offshoring. In line with their findings, we find that training can also have large effects to facilitate transitions to tight occupations. Importantly, this rules out the concern that government-sponsored retraining would only have a windfall effect to firms in tight occupations, by which employers would hire the workers even in the absence of retraining. Additionally, our results provide a clear warning against short retraining that does not seem to improve the job seekers' prospects.

Section 1 introduces a conceptual framework that allows us to study the effects of retraining and search-redirection policies in shortage occupations. Section 2 presents the context of and the protocol of the correspondence study. Section 3 shows the results. Section 4 compares the cost-effectiveness of retraining and redirection interventions from the perspective of the government. Section 5 discusses takeaways for policy and how future research can pursue the comparison.

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.

[8] Leduc and Tojerow [2025] study the effects of simultaneously providing information on shortage occupations and on retraining opportunities to job seekers. Katz et al. [2022] analyze the large positive impacts of sectoral employment programs that complement occupational training with upfront screening, soft skills training, and wraparound services targeting youth without college education, similar to the population in our correspondence study.

1 Conceptual framework: the impact of retraining vs. redirection as a function of labor-market tightness

In this section, we present a simple partial equilibrium to analyze how variation in labor market tightness affect the job-finding rates of trained applicants, by comparison with untrained applicants.[9] This model formalizes the trade-off according to which in shortage occupations: (i) employers are eager to hire workers, so that retrained workers are likely to be hired, (ii) employers have a low bar, so that redirecting untrained workers may be enough.

We consider a matching model in which workers and employers search for each other in a labor market with frictions. Employers post jobs, workers send applications to these jobs, and employers screen these applications to decide which applicants to call back. In what follows, we focus on employers' callback decisions as a function of candidates' perceived productivity and the tightness of the market for the posted job. To keep things simple, we assume that the productivity y_{ij} of applicant i in 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, based on the worker's application file (e.g., résumé credentials, education, experience, training), and η_j is a job-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 labor market l. If the perceived productivity of the match y_{ij} exceeds $y^*(\theta_l)$, applicant i will be called back. Formally, applicant i is called back if and only if $y_{ij} > y^*(\theta_l)$. The probability of a callback from the applicant's point of view, integrating over the distribution of η_j, is thus given by

$$p_{il} = F[y_i - y^*(\theta_l)],$$

where $F(\cdot)$ is the cumulative distribution function of $-\eta_j$.

We assume that retraining increases applicants' perceived productivity y_i, thereby increasing their probability of being called back, p_{il}. The question we ask is: how does the impact of retraining depend on labor market tightness? In other words, how does the derivative of p_{il} with respect to y_i depend on θ_l? To answer this question, we need

[9] Proofs of the results can be found in Appendix A.4.

to assess the derivative of the productivity threshold y^* with respect to θ_l. Intuitively, firms facing 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 A.4).

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 $f(\cdot)$ is the probability density function of $-\eta_j$.

Focusing on the case in which $\frac{\partial y^*}{\partial \theta_l} < 0$ (employers lower the threshold in tighter markets), the sign of the cross-derivative depends on the shape of f. Assume that f is unimodal—first 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 trade-off in targeting more or less tight markets with retraining.

- Retraining may be more effective in contexts where employers are eager to hire workers.
- If employers already have a bar so low that they would hire anyone, training should have a relatively small impact.

Both intuitions are valid; it simply depends on where we are located on the $y_i - y^*(\theta_l)$ line. Figure 1 illustrates this reasoning graphically by showing how the impact of training may vary as a function of labor market tightness.

[FIGURE 1 ABOUT HERE]

Figure 1 also helps summarize the main prediction of the model. In tight markets, firms lower their hiring threshold $y^*(\theta_l)$, which mechanically increases callback probabilities for all applicants. The marginal effect of training is therefore strongest in intermediate ranges of tightness, where firms remain selective but face recruitment constraints. When markets become extremely tight, the threshold is so low that training adds little; when markets are slack, firms are too selective for retraining to compensate. This yields a clear comparative-static implication that we bring to the data in Section 3.

To test these implications empirically, we now turn to a large-scale correspondence study that measures how employers in tight labor markets value retraining relative to prior occupational experience.

2 Correspondence study: context and protocol

For the purpose of the study, all fictitious candidates have completed, as part of their initial education, a standard two-year vocational track. 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 vocational training in a 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 vocational training systems in France.

2.1 The French vocational training landscape

In France, schooling is mandatory from ages 3 to 16. After five years of elementary school and four years of middle school (*collège*), students enter high school (*lycée*), which lasts three years. At this stage, they choose among three main tracks: the *general* (entirely academic), the *vocational* (focused on job-specific skills) or the *technological* (combining elements of both tracks). At the end of high school, students in all three tracks can take the national *Baccalauréat* exam which grants access to higher education.[10] Students in the vocational track, however, may instead complete a shorter, two-year training program leading to the *Certificat d'aptitude professionnelle* (CAP). The CAP is a vocational credential that prepares students for entry-level skilled positions across about 200 different occupations.[11] It typically combines classroom instruction with practical training through apprenticeships in firms. The prevalence of apprenticeships varies across occupations; consequently, some of the occupations we study include apprentices while others do not.

[10] The *Baccalauréat* is a qualification roughly comparable to a high school diploma plus college entrance examination in the United States.

[11] Students who obtain a CAP can later continue their studies toward the vocational *Baccalauréat*, but in our sample of fictitious applicants, none of them follow this path.

The profiles we designed were born in 2000 and completed their initial education with a CAP in 2017.[12] Because they do not continue their studies up to the *Baccalauréat*, these individuals fall within roughly the bottom quartile of their age cohort in terms of educational attainment. However, their vocational qualification sets them apart from students who leave school without any credential beyond middle school, a group representing about 10% of each cohort. In France, one to four years after leaving school, the unemployment rate among young workers holding a CAP degree is only slightly higher than that of workers with a *Baccalauréat* (21.9% and 18.3% in 2022, respectively). This relatively small difference reflects the labor-market orientation of the CAP program, which is designed to provide practical, job-ready skills.[13] Employment prospects vary considerably among CAP graduates, depending on their occupational specialization. In the service sector, for example, across eight occupational fields, employment rates six months after graduation range from 13% (in administration, communication, and information) to 43% (in transportation, logistics, and warehousing).[14]

In summary, the individuals in our study hold the lowest level of vocational qualification within the French education system. While they are better positioned in the labor market than those who leave school without any credential or only a middle-school diploma, they still face relatively high risks of unemployment and their employment prospects differ markedly across occupations and sectors.

This heterogeneity motivates our focus on continuing education and adult training opportunities for CAP graduates. The adult vocational training system in France is a vast sector involving a large number of actors. It includes up to 75,000 public and private training providers ("organismes de formation"). Training may also be provided in-house by large firms with dedicated human resources staff, as well as within the formal education system. Training is financed primarily by employers (who are legally required to devote a minimum share of their payroll to training), but also by public employment agencies and by the *Régions*—the fifteen regional governments into which France is administratively divided.

The system is partly segmented, as some training providers specialize in programs for unemployed job seekers, while others primarily operate within firms to train employed

[12] In additional analyses and robustness checks, we vary age and work experience. See Section 3 for details.

[13] For comparison, one to four years after leaving school, 40.8% of high-school dropouts are unemployed; the unemployment rate is 11.1% among workers with short postsecondary training, and 7.2% among those with long higher-education training. The overall average is 14.5% (education.gouv.fr, Figure 1, p. 288).

[14] See education.gouv.fr, Table 4, p. 281. There is also a sizable gap between graduates trained exclusively in classrooms and those who completed an apprenticeship.

workers. An important distinction concerns whether a given training program leads to a nationally recognized degree or certification ("formations diplômantes et certifiantes"), which typically correlates with the duration of the program.

In our study, there is heterogeneity among movers in the extent to which they retrain, leading to different types of certification. Among short-retraining movers, participants complete short-term, career-oriented programs tailored to specific occupations or skill profiles. These certifying programs usually last about a week and are designed mainly for individuals already in the workforce. They lead to a certification recognized by industries and registered in the *Répertoire National des Certifications Professionnelles* (RNCP, the National Directory of Professional Certifications).

By contrast, long-retraining movers undertake programs leading to a CAP or a *Titre professionnel* — qualifications at a similar level in the French system. These programs typically last less than a year (around nine months) and include a short internship in a company.

2.2 Target and source occupations

We study occupational mobility towards "target" occupations in high demand (i.e., tight occupations, where few candidates have the required experience or initial training relative to labor demand), 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, based on a composite indicator developed by the French Ministry of Labor. The indicator takes into account three dimensions: the hiring difficulties reported by employers, the ratio of job vacancies to the number of job seekers, and the ease with which job seekers can find employment.[15] We exclude certain occupations: those that require high or medium levels of qualifications; with a strong employment-training link (for instance, specific training required by law); for which there are no appropriate medium or short-duration training options;[16] not experiencing national-level tightness;[17] with a volume of job vacancies too low to create a sample size

[15]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`).

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

[17]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

sufficient for statistical analysis.[18]

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 within 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 A.1). Next, we exclude potential "source" 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 lists the selected occupations.

[TABLE 1 ABOUT HERE]

2.3 Resume design

This section summarizes the main design choices. Appendix A.2 provides more details, and Appendix A.3 displays two examples of CVs with their cover letter used in the correspondence study.

2.3.1 Candidate training profiles

Fictitious résumés were submitted to vacancies posted on the French national employment agency website, with systematic variation in candidates' educational background and retraining history. Four training profiles were defined: incumbents with a vocational certificate (a "CAP" which corresponds to the typical education for the occupation) and experience in the target occupation, and movers from neighboring occupations, either untrained, short-trained, or long-trained. The long and the short retraining

vacancies and low number of high-tightness occupations.

[18]Given the relative proximity of the start of our study (November 2021) to the Covid crisis, we also took care to select occupations in which labor demand appeared to have recovered by the end of 2020. Based on job posting 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 posting volumes compared to pre-Covid levels, i.e., below the third quartile of this ratio, were excluded.

programs differ by their duration (6 to 12 months vs. 2 to 5 days) and their costs (€6,000 vs €800). The characteristics of the training programs are summarized in Table 2.

[TABLE 2 ABOUT HERE]

2.3.2 Other credentials

Four résumé "characters" were constructed and cross-randomized with the training profiles to ensure variation while preventing detection. Each character varied in layout, identity, hobbies, and cover letter. All résumés reported identical core information: age (21 years old[19]), immediate availability, possession of a driver's license and vehicle, and standardized soft skills. Professional experience and hobbies were drawn from existing online CV databases and adjusted for consistency across occupations.

2.4 Experimental implementation and data collection

Identification of job vacancies The main selection criteria for job postings relate to the date of publication of the posting (we prioritize recently published postings), the type of contract for the position (fixed-term or permanent) and the search area (metropolitan France, excluding Corsica).[20] Other criteria are taken into account, mainly to avoid employer detection. In particular, postings from companies included in the candidates' profiles are excluded, as well as postings from a company that has already been tested. Similarly, we exclude postings 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 applications is reported in Appendix Figure A.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.[21] Callback events are almost instantly redirected to an online spreadsheet consulted by the research assistants every evening. To limit inconvenience for genuine employers or candidates, interview proposals are quickly declined.

[19]In the extended analysis we add a profile to vary age, see Section 3.3.

[20]Postings located in Corsica or in the overseas territories are excluded from our search area to limit the risk of our résumés being detected.

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

Implementation of study A total of 6,668 applications were sent in response to 1,743 job vacancies (Table 3). 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 and until completion in April 2024, we over-represented the last three occupations to obtain more robust results for female-dominated occupations, as presented by Appendix Figure A.1.

[TABLE 3 ABOUT HERE]

The job postings to which applications were sent were chosen randomly and are representative of postings that are found in these occupations. Their characteristics are detailed in Appendix Table A.1. It is interesting to note that a CAP in the target profession is required in half of the job ads, which may limit the positive response rates for untrained movers.

3 Main results

3.1 Impact on callback rates

Figure 2 displays the callback rates 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.

[FIGURE 2 ABOUT HERE]

As we might expect, incumbent candidates have the highest likelihood of a positive callback (56%). Long-retraining mover candidates are called at a high rate (46%). The difference relative to the incumbent suggests a penalty to changing professional direction. However, a full retraining closes a sizable part (two-thirds) of the gap in callback between the incumbent and the untrained mover. The lowest callback rate is among the untrained movers (28%). Strikingly, however, there is no significant difference in callback rate between these candidates and the short-retraining movers (about 27%). This suggests that short-term training does not convince an employer of skills (or motivation) for the target occupation.

Table 4 shows the results of the regression analysis. Column 1 computes the gaps across the four different profiles relative to the incumbent. In Column 2, we include detailed controls for the résumé identifier, the order in which the résumés were sent, whether the candidate indicates moving to the region, and the distance between the candidate's address and the job location. Similarly, in Column 3, we further include application and vacancy fixed effects. The three columns provide very similar conclusions, aligned with that of Figure 2.

[TABLE 4 ABOUT HERE]

3.2 Differences across occupations

Appendix Figure A.3 and Tables A.3-A.8 highlight some interesting variation across occupations, even though the main patterns remain. In all occupations, with the exception of restaurant employees, callback rates of the incumbent candidate are above 50%, which suggest a high tightness.[22] 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, these occupation share the pattern of Figure 2, despite large differences in gender composition and industry. This suggests that the results have some external validity among tight, middle-skilled occupations.

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, we introduce a candidate with a profile similar to the incumbent but born a year later (i.e., three years of experience, excluding initial training). This profile likely provides an upper bound of the effect of an additional year of professional experience.[23] This is important as the incumbent profile differs

[22]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.

[23]The difference in callback between the incumbent and the younger candidate is due to the sum of an age and experience effect, which is likely larger than the effect of experience alone. We chose to vary

from the trained mover by having spent less time in training, and up to one more year working. Second, we introduce a candidate with a profile similar to the incumbent aged 17 and just entering the labor market.

The results are presented in the last two lines of Table 4. 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 percentage point lower than the incumbent), having no experience decreases callback significantly (by 19 percentage points). Taking into account that these are upper bound for the effect of experience, the comparison between incumbents with four vs. three years of experience shows that at most one third of the gap between the incumbents and the long-retraining movers can be explained by the additional year of work experience.

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.

[FIGURE 3 ABOUT HERE]

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, incumbent candidates are preferred over long-retraining movers, with a stable gap. Similarly, the large disadvantage of the other profiles persists over time.

3.4 Differences within occupations by tightness

Our empirical design included an important feature that allows us to bring the model to the data: we selected occupations for which tightness exhibits large variations across local labor markets. Figure 4 illustrates that variation. We measure tightness as the ratio between the number of vacancies and the number of job seekers (V/U) in each occupation. We see that this ratio may vary by a factor of three in adjacent jurisdictions (*départements*). Because untrained and short-training movers have essentially the same callback rates, we pool them together in the analysis to increase statistical precision. We also pool one-year younger profiles with the group of incumbent candidates.

[Figure 4 ABOUT HERE]

age and experience simultaneously, as changing the candidate's experience without changing his age would have sent a negative signal and made the comparison hard to interpret.

Figure 5 plots non-parametric estimates of the relationship between log-tightness and callback rates, by profile.[24] We first check empirically that callback rates are increasing in log-tightness for the three profiles. We find that the returns to long-retraining (compared to untrained movers) are positive at all tightness level, but tend to increase with tightness. This suggests that retraining is more effective in tighter markets.

Appendix Table A.9 provides regression results by occupation. 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 initial training (incumbents) and tightness. To gain power, we pool occupations in Table 5. For transparency, Columns 1 and 2 pool all occupations, including restaurant employees. While the cross-effect point estimates are positive, they are not or marginally significant. In our preferred specifications (columns 3 and 4), we exclude restaurant employees who seem to obey a different logic. In all specifications, occupation dummies are included to obtain identification from geographical variations in tightness alone, and not from comparisons across occupations. In addition, Columns 2 and 4 add controls for firm characteristics (firm size and firm total factor productivity). The local composition of firms may indeed be correlated with tightness. By adding controls for firm size and productivity, interacted with application type (incumbent and long retraining mover), we check that the heterogeneous effects by tightness are not spuriously driven by local variations in firms' characteristics. We find a meaningful and significant cross-effect. The impact of long retraining (compared to untrained or short-training movers) is multiplied by about two ($= (0.0573 + 0.0685)/0.0685$) following a twofold increase in tightness.

[FIGURE 5 ABOUT HERE]

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 even in the tightest local labor markets in our sample. 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 government-sponsored retraining policies in those markets as a way to increase job

[24] 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.

finding rates.

[TABLE 5 ABOUT HERE]

4 Discussion: retraining vs. search redirection

The strong impact of retraining on the job-finding rates of job seekers suggests that this may be an effective policy for a government aiming to reduce the cost of occupational mismatch in unemployment insurance. An important caveat, though, is that retraining is costly (about €6,000 in our experiment), while policies aiming to redirect job search towards tight occupations have very low marginal costs when administered online, via email, or through information on websites. In this section, we perform a simple cost-benefit analysis to compare the cost-effectiveness of both policies individually. We then discuss arguments suggesting that they may be complements rather than substitutes.

4.1 Cost-effectiveness of training for the unemployment insurance

We take the perspective of unemployment insurance and focus on the balance between direct program costs and savings in unemployment-related expenditures. We abstract from general equilibrium effects and consider a steady-state labor market in which unemployed job seekers alternate between unemployment and employment spells in shortage occupations. The key distinction between retrained and nudged workers lies in their job-finding probabilities: skilled (retrained) workers find jobs at monthly rate λ_1, while unskilled workers applying to shortage occupations do so at rate $\lambda_0 < \lambda_1$. All parameters are summarized in Table 6.

[TABLE 6 ABOUT HERE]

Retraining policies entail two main costs, pedagogical costs C_{ped} and costs associated with unemployment benefits paid during training C_{UI} (lock-in effect):

$$C_{\text{train}} = C_{\text{ped}} + C_{\text{UI}}.$$

With the calibration shown in Table 6, the total cost per retrained worker equals €15,000. The benefit of retraining arises from faster transitions to employment. For the first unemployment spell, the expected reduction in unemployment benefit payments is given by

$$B_1 = \left(\frac{1}{\lambda_0} - \frac{1}{\lambda_1}\right) D_m,$$

where D_m corresponds to monthly unemployment benefits. We find that B_1 equals €5,500 under the assumed parameters. The net fiscal balance for the initial spell is

$$NB_1 = B_1 - C_{\text{train}} = -€9{,}500.$$

To account for the long-term effect of retraining, we distinguish between two scenarios:

- **Pessimistic scenario:** the job-finding advantage of retrained workers dissipates after the first unemployment spell (e.g., because unskilled workers eventually gain comparable experience or because retrained workers exit shortage occupations). In this case, retraining remains fiscally costly, with limited dynamic benefits.

- **Optimistic scenario:** the job-finding advantage persists over the entire working life. The expected discounted benefit from reduced unemployment expenditures is then
$$B_2 = \sum_{t=1}^{T} \beta^t \, 12 D_m (u_0 - u_1),$$
where u_0 (respectively u_1) is the steady-state unemployment rate for unskilled (respectively skilled) workers.

Under the calibration in Table 6, this yields a cumulative fiscal benefit of approximately €11,200, so that the total discounted net benefit is

$$NB_{\text{total}} = B_1 + B_2 - C_{\text{train}} \approx €1{,}700.$$

Taken together, these two scenarios provide plausible bounds for the relative fiscal performance of retraining. At one extreme, retraining is a costly intervention whose benefits dissipate quickly; at the other, it is a fiscally positive investment with long-run returns that offset initial expenditures.

We should note that the optimistic scenario for the cost–benefit analysis of training is sensitive to the choice of the $u_0 - u_1$ gap in unemployment rates between skilled and unskilled workers, as these gains are assumed to accrue over an entire working life (40 years). Our preferred calibration (cf. Table 6) uses the gap between the 2024 unemployment rates of qualified versus unqualified employees (4.1 percentage points). However, an alternative calibration choice would be to use the unemployment rates of skilled versus unskilled blue-collar workers, since three out of the six occupations in our study are blue-collar occupations. This gap is larger over the 1982–2024 period for which we have data (7.1 percentage points). Setting $u_0 - u_1$ to 7.1 percentage points would yield an upper bound for the total discounted net benefits of €9,900. However, we find it unrealistic that a single retraining spell would reduce the unemployment rate of beneficiaries by 7 percentage points over the course of a lifetime, so we keep a gap of 4.1 percentage points for the main scenario.

4.2 Retraining and job-search redirection: complements or substitutes?

Our computations show how redirection and retraining interventions act on distinct margins — redirection nudges as low-cost, low-impact tools, and retraining as a high-cost, potentially high-return investment. From the government's perspective, the two policies may then be useful instruments appropriate for different objectives (for instance, a short-term response to rising unemployment versus a long-term shift in the industrial structure), rather than substitutes.

The two interventions may be complementary in a more profound sense. Indeed, our analysis has abstracted from labor supply aspects: to what extent do job seekers take up retraining offers and redirection recommendations? While the literature on recommender systems stresses their low cost, few experiments have shown quantitatively large effects of recommendations on job finding rates.[25] Given our finding that firms are willing to hire redirected job seekers, the binding constraint on redirection policies may be the ability to convince a substantial share of job seekers. A potential avenue considered for instance by the French public employment service is to have case workers promote recommendation algorithms. This however makes the intervention much more costly. Overall, it may be that, at the limit, nudges and information provision, even with human mediation, cannot shift behavior substantially.[26]

[25] On the high end, Belot et al. [2022] and Belot et al. [2023] show that occupational referrals increase the probability of securing a stable job by 19 to 31% for those using the platform, with especially large effects observed for long-term unemployed individuals and job seekers from structurally slack labor markets. Altmann et al. [2023] report up to a 4-4.5% increase in labor earnings and hours worked, but no significant impact on job finding rates. Hensvik et al. [2023] and Behaghel et al. [2024] find much smaller effects when directing job seekers' applications toward specific posted vacancies (a 0.5% increase in employment, and a 1% increase in job finding rates, respectively). Ben Dhia et al. [2022] find no employment effects from encouraging job seekers to use a private online platform offering tailored job search tips.

[26] An option studied by Leduc and Tojerow [2025] is to simultaneously provide information on shortage occupations and on retraining opportunities to job seekers. However, they find in their experiment that this did not boost enrollment in occupational training for shortage jobs, and that while job seekers

5 Conclusion

What are the takeaways of this research for policy? The potential of recommender systems has attracted considerable interest from public employment services as a means to reduce occupational mismatch by encouraging job seekers to broaden their search. This raises an important question: is there still room for government-sponsored retraining programs? If firms that are unable to fill vacancies in shortage occupations are willing to hire job seekers switching occupations, public employment services may be less well-positioned than firms themselves to provide adequate post-hire training. Our results, however, indicate that while firms in tight labor markets do invite untrained occupational movers for interviews, there remains a substantial "retraining premium" — a twofold increase in callback rates for trained candidates. This clear ranking of firm preferences intensifies further as labor market tightness increases. In sum, governments seeking to reduce occupational mismatch have a strong case for deploying both tools — retraining and redirection — as complementary rather than substitutive policies.

We fully acknowledge that our results are not sufficient for a complete comparison between retraining and redirection policies. Further research would be particularly valuable in two main directions. First, the question of scale. The large-scale expansion of each policy faces different constraints. For training policies, scalability requires an adequate supply of high-quality training programs and raises concerns about financial incentives and oversight for publicly funded providers. For redirection policies, the key question is behavioral: are there enough job seekers responsive to informational nudges? How can these interventions be designed to reach beyond the marginal, already-motivated job seekers? Second, the time horizon. The current focus on interview rates must be complemented by evidence on long-term outcomes. While the long-run effects of training are relatively well-studied, little is known about the trajectories of nudged occupational movers — whether they receive firm-provided on-the-job training, and whether they remain in their new occupations. These remain important open questions for future research.

shifted their search towards high-demand occupations, employment remained unchanged.

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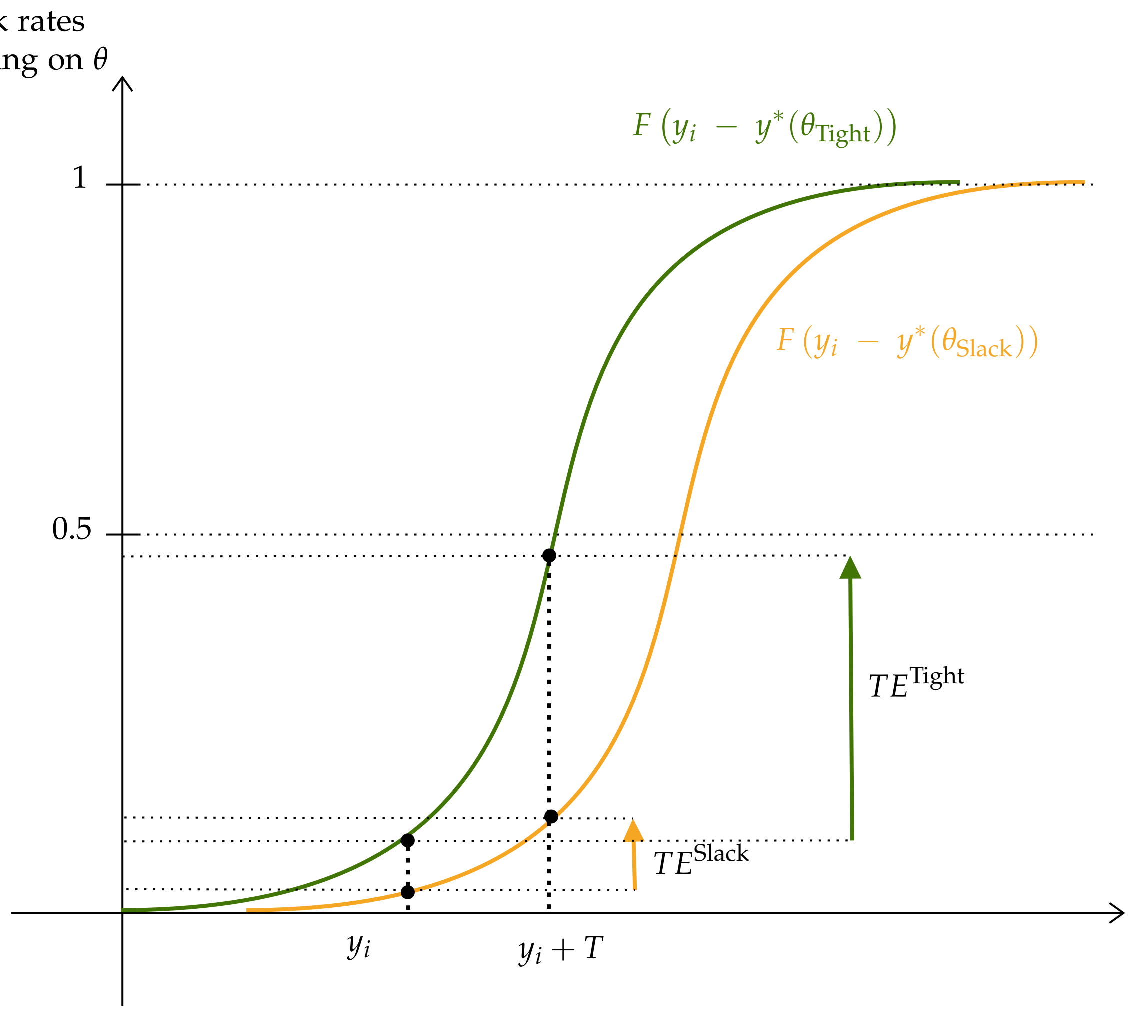
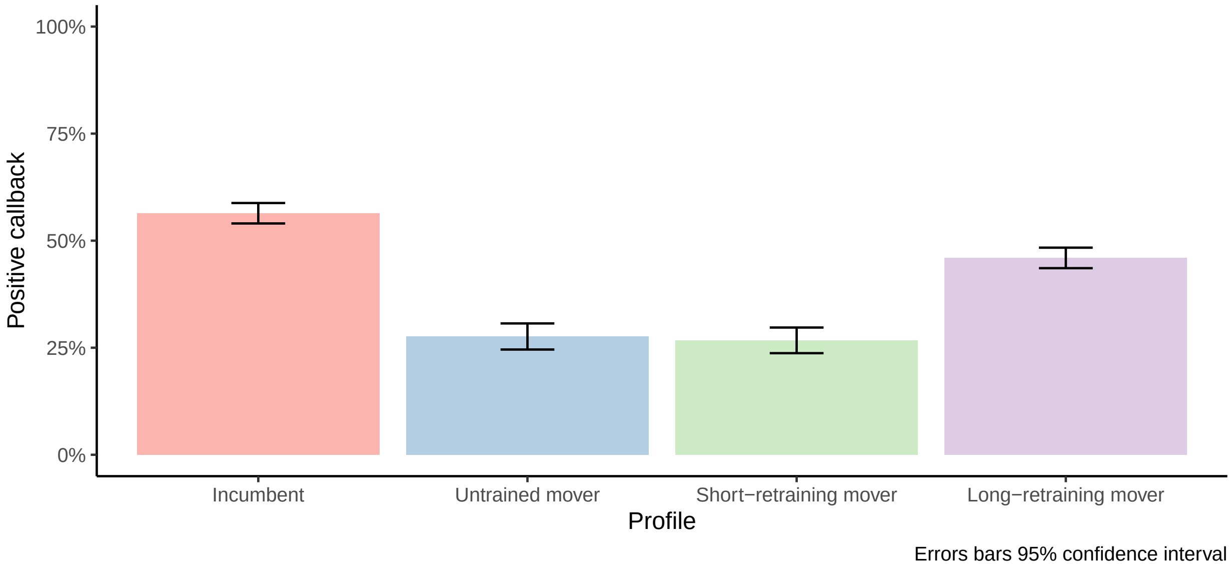
Figures

Figure 1: Illustration of how the impact of training may vary as a function of labor-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 2: 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. For instance, 56% of employers respond positively to the incumbent applicants.

Figure 3: Survival analysis, by profile

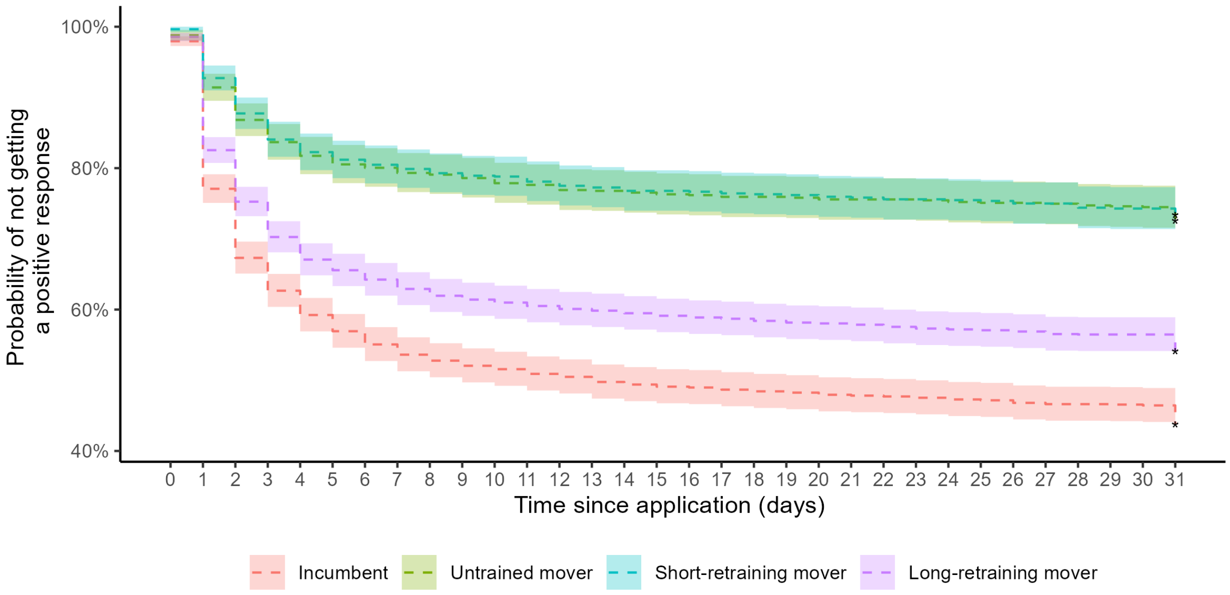


Figure 4: Tightness (V/U) by local labor market

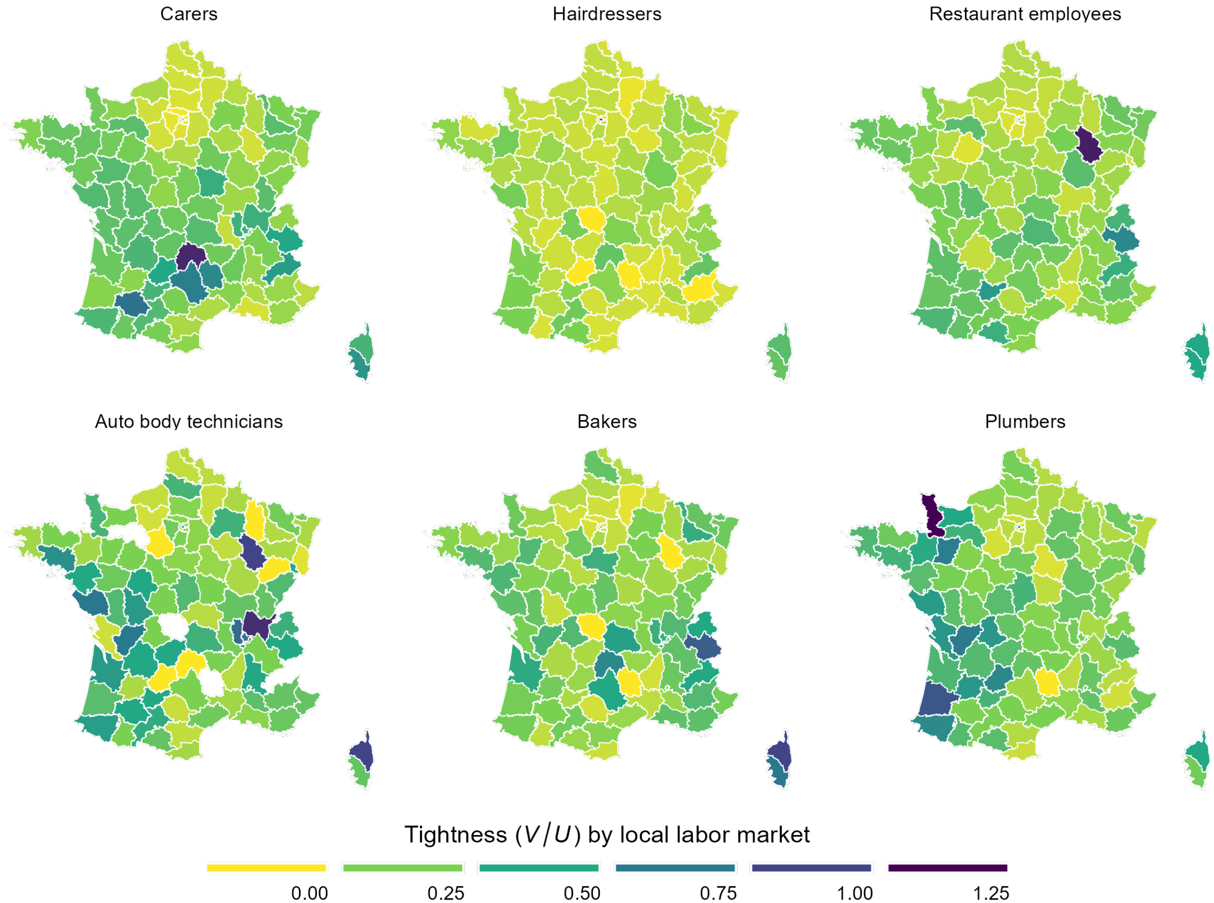
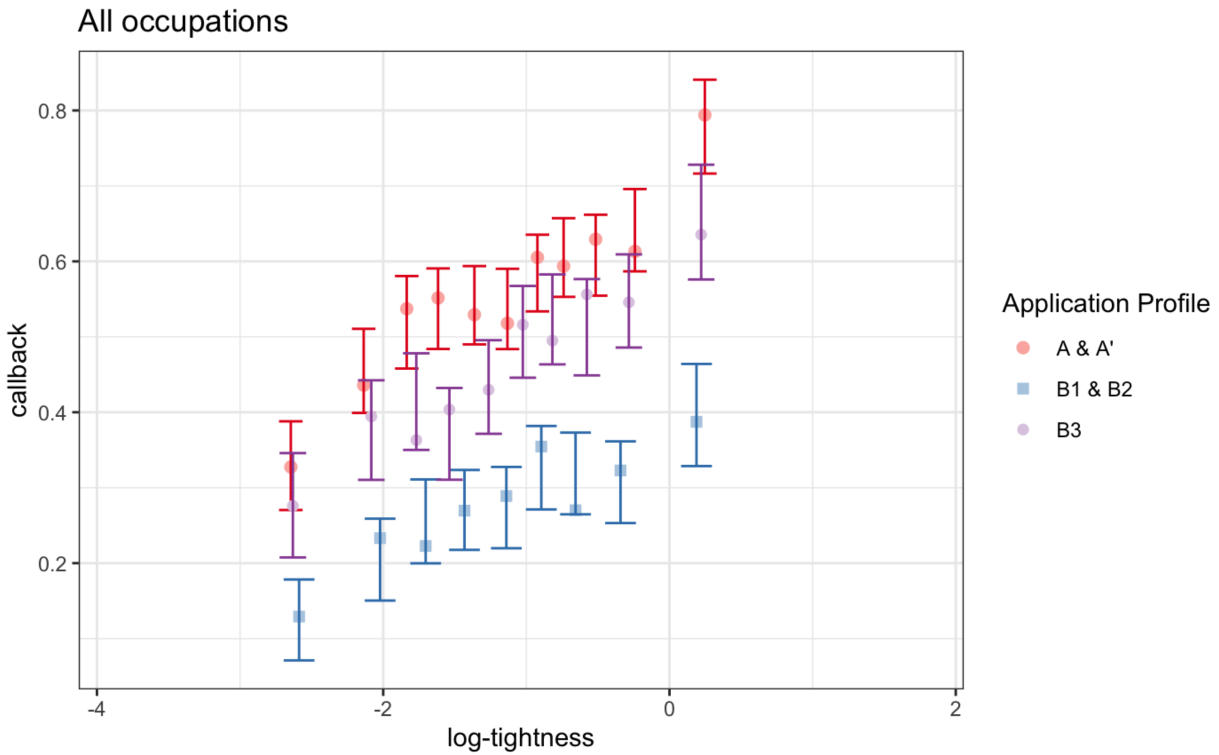


Figure 5: HETEROGENEITY OF CALLBACK RATES ALONG TIGHTNESS



Tables

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

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

Table 2: Characteristics of training received by retrained movers

	Short retraining			Long retraining		
	Name	Duration	Av. price	Name	Duration	Av. price
Carers	Emergency care and first aid training	2 days	250 €	Nursing assistant	12 months	1500 €
Hairdressers	Online hairdressing course	5 days	700 €	CAP hairdressing	9 months	4000 €
Restaurant employees	Food hygiene HACCP	2 days	500 €	CAP restaurant and café-hotel service	12 months	9000 €
Auto body technicians	Introduction to dent removal	3 days	1000 €	Professional certificate auto body painter	7 months	12 000 €
Bakers	Introduction to bakery and pastry	4 days	1100 €	CAP baker	9 months	9000 €
Plumbers	Introduction to plumbing	4 days	1100 €	Professional certificate plumber-heating technician	7 months	10 000 €
Total		3 days	775 €		9 months	5875 €

Table 3: Job postings and number of applications being sent, per occupation

	Nb job postings	Nb of applications being sent
Female-dominated occupations		
Carers	283	1 101
Hairdressers	280	1 090
Restaurant employees	293	1 114
Male-dominated occupations		
Auto body technicians	303	1 144
Bakers	294	1 112
Plumbers	290	1 107
Totals	1 743	6 668

Table 4: Effect of training on probability of callback

	OLS (1)	+ controls (2)	+ FEs (3)
Long-retraining mover	-0.1038***	-0.0883***	-0.0969***
	(0.0172)	(0.0172)	(0.0135)
Short-retraining mover	-0.2962***	-0.2732***	-0.2860***
	(0.0195)	(0.0214)	(0.0189)
Untrained mover	-0.2875***	-0.2641***	-0.2796***
	(0.0197)	(0.0217)	(0.0197)
Incumbent - 3 years of experience	-0.0340	-0.0352	-0.0282
	(0.0211)	(0.0226)	(0.0185)
Incumbent - no experience	-0.1937***	-0.1842***	-0.1786***
	(0.0206)	(0.0223)	(0.0182)
Incumbent mean	0.5638	0.5638	0.5638
Controls		✓	✓
Application date FE			✓
Vacancy FE			✓
R^2	0.05130	0.06843	0.65565
Observations	6,668	6,668	6,668

Notes: Each column displays a separate regression OLS of the indicator variable equal to 1 if the application received a positive callback on the different treatments (the reference is the incumbent profile). Column (1) includes no control. Column (2) includes the CV profile, the order in which the CVs were sent, the fact that the candidate explicitly mentioned that he/she is moving in the region, the fact that he/she graduated from a CFA, and the time of commute between the candidate's address and the job location. Column (3) includes application date and vacancy fixed-effects. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (Application date-Vacancy) standard-errors in parentheses. The reference profile (incumbent) has four years of experience. The bottom two regressors correspond to subtreatments with three years of experience instead of four (candidate aged 20 instead of 21) and no experience (candidate aged 17).

Table 5: Heterogeneity along tightness

	All occupations		All but Restaurant Empl.	
	(1)	(2)	(3)	(4)
Log-tightness	0.0889***	0.0938***	0.0638***	0.0685***
	(0.0167)	(0.0182)	(0.0184)	(0.0204)
Log-tightness x Incumbent	0.0485**	0.0385	0.0687***	0.0543**
	(0.0228)	(0.0246)	(0.0253)	(0.0274)
Log-tightness x Long retraining mover	0.0361	0.0315	0.0606**	0.0573*
	(0.0253)	(0.0269)	(0.0278)	(0.0298)
Occupation Indicators	✓	✓	✓	✓
Additional controls		✓		✓
Observations	5,625	5,625	4,710	4,710

Reference type: Untrained and short-retraining movers.
Additional controls: Candidate dummy, sending order of applications, commute time to firm, recent move indicated, firm size and productivity. All controls are interacted with profile category. Incumbent candidates without experience are excluded from the table.

Table 6: Parameter values used in the cost–benefit calibration

Parameter	Symbol / Value	Description
Job-finding rate (unskilled)	$\lambda_0 = 1/11$	Monthly job-finding probability for unskilled applicants to tight occupations
Job-finding rate (skilled)	$\lambda_1 = 2/11$	Monthly job-finding probability for retrained (skilled) applicants
Unemployment rate (skilled)	$u_1 = 0.070$	Steady-state unemployment rate of retrained workers
Unemployment rate (unskilled)	$u_0 = 0.111$	Steady-state unemployment rate of unskilled workers
Pedagogical cost of training	C_{ped} = €6,000	Cost of providing training
Monthly UI cost	D_m = €1,000	Monthly unemployment benefit
UI cost during training	C_{UI} = 9 × €1,000 = €9,000	Unemployment benefits paid during training period
Discount factor	$\beta = 0.97$	Annual discount factor
Duration of working life	$T = 40$	Remaining years of working life considered

Notes: here, we provide details on our calibration choices for the main parameters of the exercise.
λ_0, λ_1 : the monthly job finding rates for the unskilled applicants (λ_0 is calibrated based on the estimated expected duration of an unemployment spell in the second quarter of 2024 (estimation by the French public unemployment services), equal to about 11 months for all job seekers and for job seekers who enter unemployment after the end of a definite duration contract (making them eligible to unemployment benefits if, e.g., the contract lasted more than 6 months). Then, λ_1 is set to twice the value of $\lambda_0 = 1/11$ based on the ratio between callback rates of incumbents and/or long-retraining movers to the one of the untrained mover in our study (which is about 2, cf. Figure 2).
Source: France Travail – Durée de chômage (2e trimestre 2024).
u_0, u_1 : as section 4 makes it clear, what matters for the exercise is the calibration of the gap between u_1 and u_0 rather than their levels. Our preferred calibration uses the gap between the unemployment rate of qualified vs. unqualified employees computed by the French national statistical office in 2024 (11.1% vs. 7.0%). This gap of 4.1 percentage points also corresponds to the average gap in unemployment rates between these two populations over the 2015 to 2024 period (the longest period for which this contrast is reported by the statistical office). Recall that in our most optimistic scenario for the cost-benefit of training, the gains derived from this gap in unemployment rates are assumed to accrue over a whole working life (40 years)—making our upper bound for the net benefits of training programs quite sensitive to the $u_1 - u_0$ value. An alternative calibration choice would be to use the unemployment rates of skilled vs. unskilled blue collars—since three out of six occupations in our study are blue collar occupations. This gap is much larger in 2024 (8.9 percentage points) and over the 1982-2024 period for which we have data (7.1 percentage points). See main text (section 4) for a discussion of the consequences on our upper bound.
Source: Insee – Emploi, chômage, revenus du travail (Édition 2025)
C_{ped} : cf. Table 2.
D_m: following the simulator of the French public employment services, the monthly unemployment benefits of an individual who would register as unemployed after a three-year (full time) definite duration contract paid at the minimum wage would be just a little above 1000 euros per month.
Source: France Travail – Simulateur (used on Nov 1, 2025).

A Appendix

A.1 Identifying Neighboring Occupations

The identification of neighboring occupations builds and improves on the algorithm developed in Behaghel et al. [2024]. The algorithm assigns a real value, called *occupational distance*, to each pair of occupations (based on occupation codes, ROME). This measure reflects how easily workers can transition between jobs.

The ROME classification already contains a *Mobility* section listing possible job transitions, but these recommendations are limited and may overlook in-demand occupations in a given local labor market. The occupational distance measure extends this list, offering broader reorientation possibilities.

To do so, the algorithm combines ROME descriptors with transition data from the Annual Social Data Declaration (DADS) and Pôle emploi's Historical File (FH). These sources capture both job changes of registered job seekers and transitions occurring outside Pôle emploi.

Algorithm Functioning The algorithm predicts observed transitions (from DADS and FH-DADS) using information from ROME job descriptions.

If predictions rely too heavily on observed transitions, the model risks reproducing existing biases (overfitting). If too close to ROME classifications, it may miss relevant transitions beyond narrowly defined similarities.

Features Used

- Structured fields: Basic skills, Specific skills, Work environment.
- Unstructured fields: Definition, Job access, Working conditions (processed as bag-of-words).
- The *Mobility* section is reserved for evaluation.

Training Sample A supervised learning approach is used, with labeled data representing the share of transitions from one occupation to another. The training sample is constructed by:

1. Aggregating transition triplets (origin, target, number of transitions) from FH and DADS.
2. Normalizing to compute the share of transitions from each origin occupation.
3. Selecting 300 origin occupations (weighted by transition volume).
4. Randomly drawing 1,500 occupation pairs, stratified by transition share (high, medium, low, very low).

This sample is intentionally biased toward stronger transitions, since those are rarer but more important to detect. To avoid overfitting, performance is validated on unseen pairs, and training is stopped early if necessary.

Learning Method The main method is **lasso regression**, which penalizes large coefficients and prevents overfitting. Results were compared with random forests and regression trees (CART). Lasso was preferred for its interpretability and robustness given the limited dataset.

Results Across all versions, text-based variables (bag-of-words features) show strong predictive power for identifying viable occupational transitions.

A.2 Detailed Résumé Design

Training of Candidates We send out several fictitious résumés to vacancy job postings on *Pôle emploi*'s website, the national employment agency, in which we randomly vary the experience and the amount of training, while keeping other characteristics comparable. For each occupation, we design fictitious résumés. We randomly vary the education and training block to create the four profiles of interest. The résumés 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 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 and has a few years of experience in the source occupation but undertakes a short vocational training in the target occupation.
- **Long-training mover** This job seeker is initially trained and has a few years of experience in the source occupation but undertakes a long vocational training in the target occupation.

The characteristics of the retraining received by the short retraining and long retraining movers are displayed in Table 2. The long and the short retraining programs clearly differ by their duration (6 to 12 months vs. 2 to 5 days) and their costs. The short retraining programs typically cost 800 euros for three days, raising the question of their cost effectiveness.

Other Credentials Four résumés are sent to each job posting. To avoid detection, we vary the credentials and the layout of these four résumés, 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 résumés in each occupation. When applying to a given job posting, we further randomize the order in which the résumés are sent.

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

Each résumé 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 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 21 years old.[27]

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 (motorcycle), as mobility is often required.

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 posting.[28]

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' résumé.[29]

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.

[27] In the extended analysis we add a profile to vary age, see Section 3.3.

[28] 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: this did not make a significant difference.

[29] 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.

A.3 Examples of Résumés and Cover Letters

Bastien PATRONYME

20-12-2003

ADRESSE POSTALE

NUMERO DE TELEPHONE PORTABLE

COURRIEL

Fraîchement diplômé du CAP Réparation des carrosseries, je suis à la recherche d'un poste de carrossier. Je suis rigoureux, très motivé et passionné par ce métier. En cours de mobilité dans la région, je suis disponible de suite. Je possède le permis et une voiture.

Expériences professionnelles

Apprenti carrossier peintre — septembre 2019 - juin 2021
ENTREPRISE 1 — Blois (41)

Réparation tout sinistre et peinture (peinture lechler). Remise en forme, notamment par débosselage, planage, ponçage, toute carrosserie endommagée. Gérer les expertises (photo expertise), devis clients, commandes de pièces défectueuses. Élaboration des factures.

Formations

CAP Réparation des carrosseries — 2021
CFA interprofessionnel du Loir et Cher — Blois (41)

Brevet des collèges — 2018
Collège Augustin Thierry — Blois (41)

Loisirs

Foot en salle, musculation

Passionné de mécanique automobile

Lectures, BD

Lettre de motivation

Objet : candidature au poste de carrossier

Madame, monsieur,

C'est avec un vif intérêt que j'ai relevé votre annonce d'emploi pour le poste de carrossier. Je souhaite évoluer dans ma carrière et mettre mes compétences au profit d'un nouveau challenge. Très motivé à l'idée de rejoindre votre entreprise, je vous fais parvenir ma candidature.

Titulaire du CAP Réparation des carrosseries, j'ai de très bonnes compétences techniques. J'ai un bon sens de l'analyse et du diagnostic des dommages. Je connais les différents équipements électriques et électroniques et les différentes structures de véhicules. Ces compétences me permettent évidemment de procéder aux réparations classiques mais également au remplacement des pièces trop endommagées sans oublier les contrôles de rigueur, grâce à divers procédés d'assemblage (rivetage, soudage...). Je fais mon travail dans le respect des différentes normes de Sécurité.

Je suis précis, ordonné et rigoureux. Autonome, j'ai aussi une facilité à travailler avec les équipes sur place. Je serais heureux d'intégrer votre entreprise et de mettre à disposition toutes mes qualités et ma disponibilité. J'ai également une très bonne condition physique.

Je me tiens à votre disposition pour vous apporter des détails complémentaires sur ma candidature.

En espérant vous avoir convaincu de l'intérêt de ma candidature, je vous exprime mes salutations les meilleures.

A.4 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 ourselves to a partial equilibrium analysis. When an employer meets a worker, the productivity of the potential match is drawn from a distribution of cumulative distribution function 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 $\Pi(y^*)$.[30] 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:

$$y^* = w + rV$$

[30] 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.

One can prove that the value of a vacancy V decreases with tightness θ — see below — 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 $y^* = w$.[31]

Deriving and signing $\frac{dy^*}{d\theta} < 0$ in partial equilibrium model 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:

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

[31] 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:

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

A.5 Additional figures

Figure A.1: Seasonality

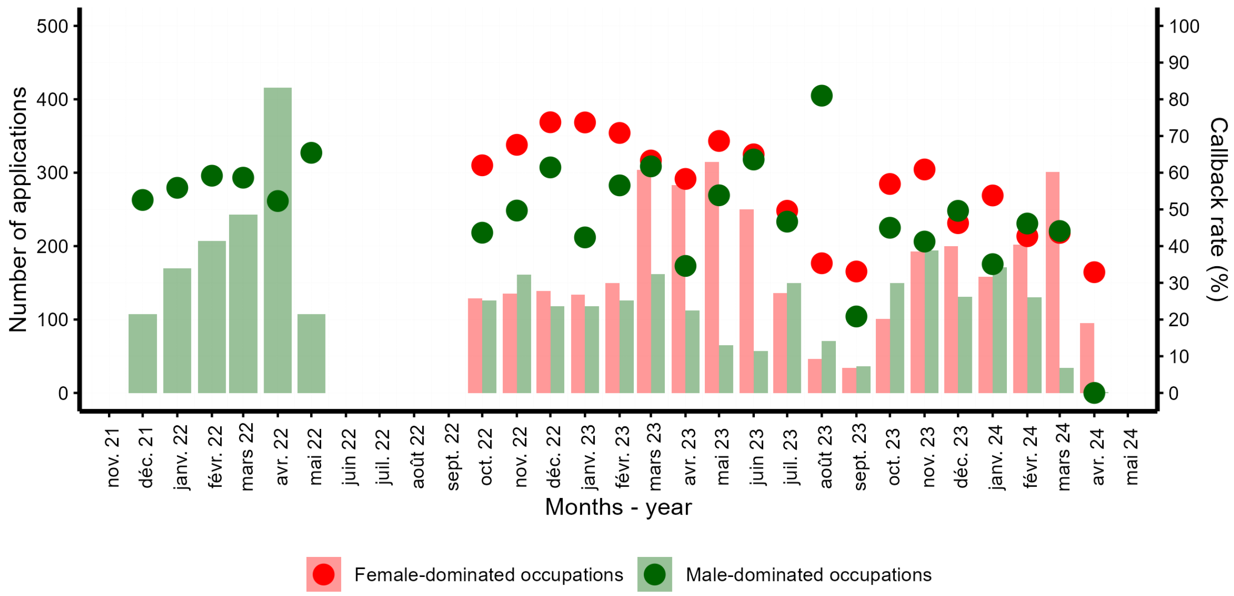
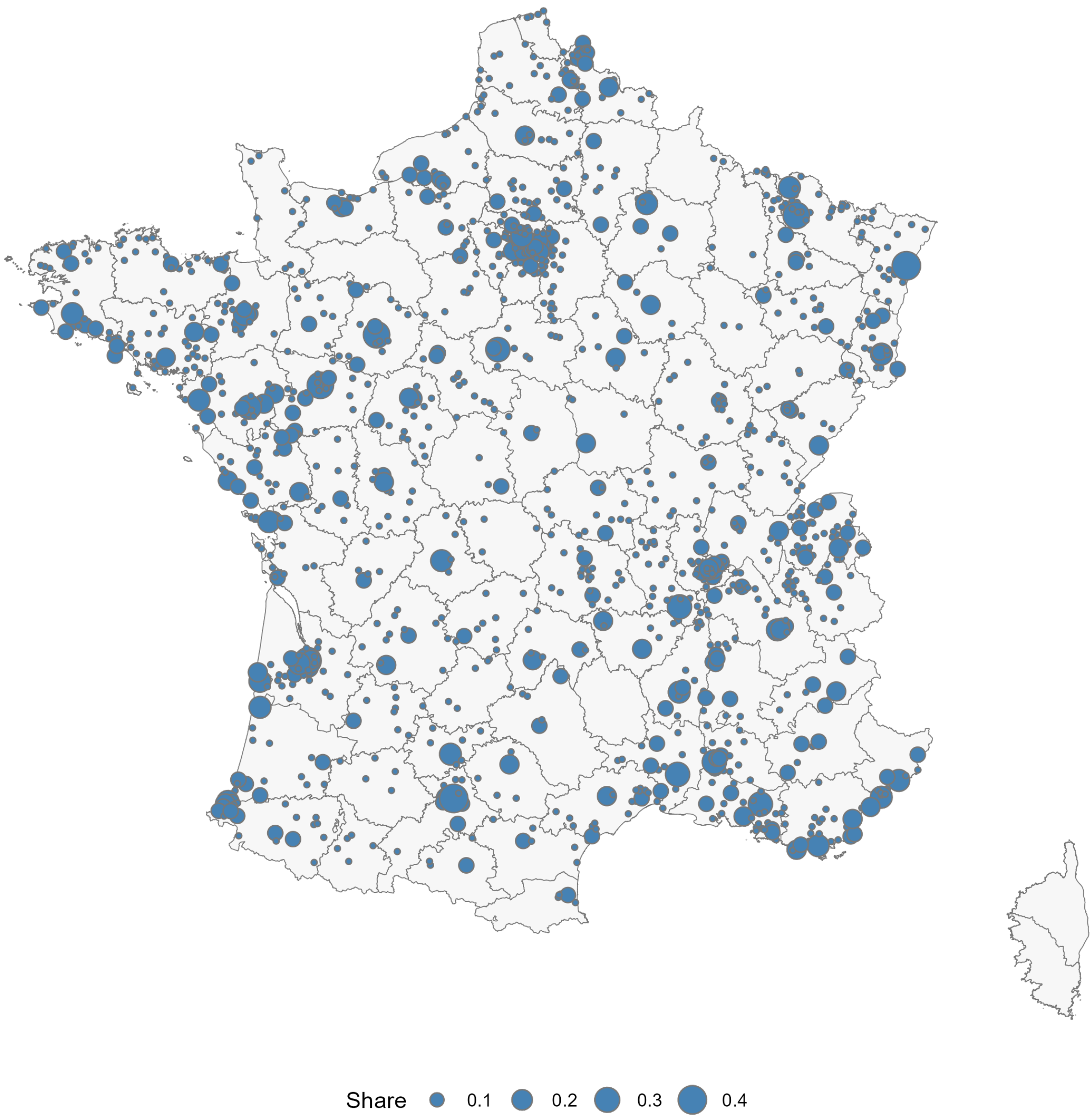


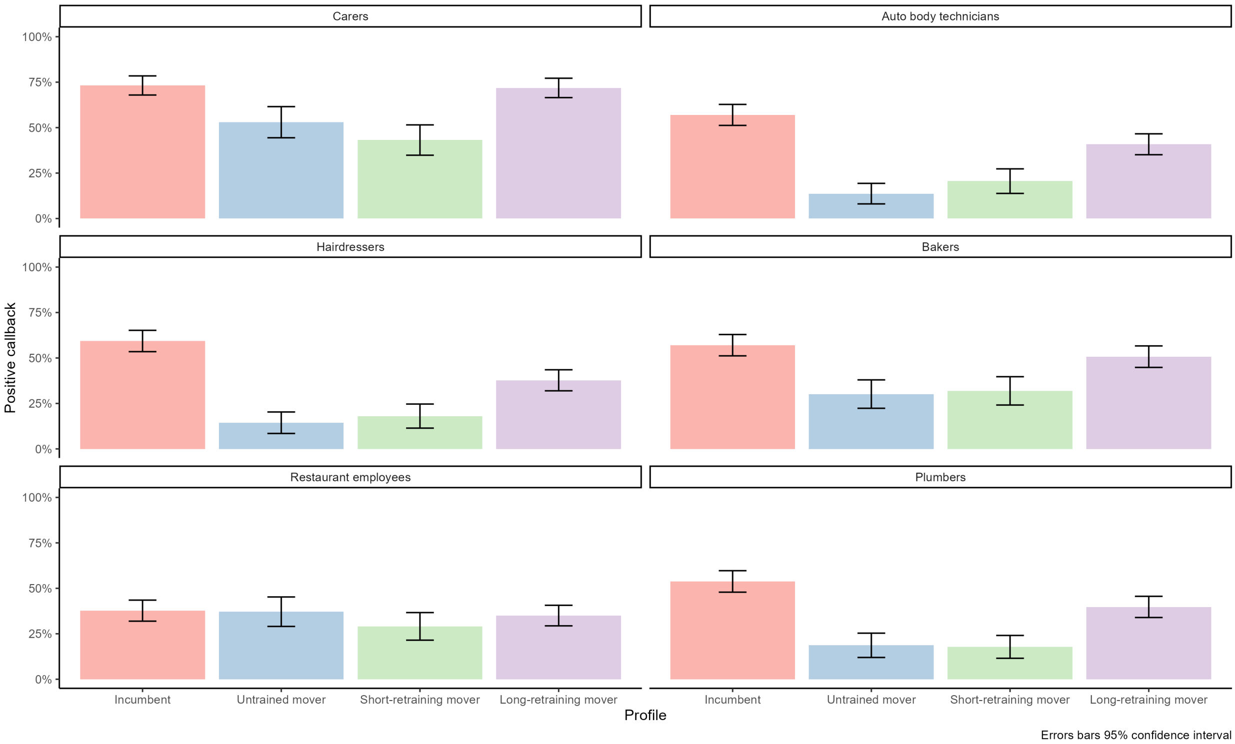
Figure A.2: Geographical spread of vacancies having received at least one application



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:

Figure A.3: Callback rates by profile and occupation



A.6 Additional tables

Table A.1: Job vacancies characteristics

	Nb of job vacancies	Proportion
Occupations		
Carers	283	0.16
Hairdressers	280	0.16
Restaurant employees	293	0.17
Auto body technicians	303	0.17
Bakers	294	0.17
Plumbers	290	0.17
CAP required		
No	701	0.40
Yes	807	0.46
Missing information	235	0.13
Experience appreciated		
No	1 000	0.57
Yes	743	0.43
Number of years of experience		
No year of experience	836	0.48
Less than one year	66	0.04
From 1 to 2 years	192	0.11
From 2 to 5 years	381	0.22
More than 5 years	87	0.05
Missing information	181	0.10
Fixed-term contract		
No	1 191	0.68
Yes	400	0.23
Missing information	152	0.09
Part-time work		
No	1 444	0.83
Yes	148	0.08
Missing information	151	0.09
Number of hours		
35 hours	1 046	0.60
Less than 35	148	0.08
More than 35	398	0.23
Missing information	151	0.09
Pre-set hourly wage		
No	322	0.18
Yes	1 264	0.73
Missing information	157	0.09
All vacancies	1 743	1.00

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

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	1 662	0.56	0.01	0.43
Incumbent - 3 years of experience	838	0.53	0.01	0.46
Incumbent - no experience	835	0.37	0.02	0.61
Long-retraining mover	1 663	0.46	0.01	0.53
Short-retraining mover	841	0.27	0.03	0.70
Untrained mover	829	0.28	0.03	0.69
Totals	6 668	0.44	0.02	0.55

Table A.3: 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
Incumbent - 3 years of experience	139	0.83	0.00	0.17
Incumbent - no experience	136	0.62	0.01	0.37
Long-retraining mover	277	0.72	0.00	0.28
Short-retraining mover	139	0.43	0.01	0.56
Untrained mover	134	0.53	0.02	0.46
Totals	1 101	0.66	0.01	0.33

Table A.4: 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
Incumbent - 3 years of experience	135	0.53	0.02	0.45
Incumbent - no experience	137	0.37	0.02	0.61
Long-retraining mover	273	0.38	0.03	0.59
Short-retraining mover	133	0.18	0.04	0.78
Untrained mover	139	0.14	0.05	0.81
Totals	1 090	0.40	0.03	0.58

Table A.5: 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
Incumbent - 3 years of experience	139	0.32	0.01	0.67
Incumbent - no experience	144	0.20	0.02	0.78
Long-retraining mover	277	0.35	0.01	0.65
Short-retraining mover	141	0.29	0.04	0.67
Untrained mover	140	0.37	0.01	0.62
Totals	1 114	0.33	0.01	0.66

Table A.6: 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
Incumbent - 3 years of experience	143	0.51	0.01	0.48
Incumbent - no experience	144	0.35	0.02	0.63
Long-retraining mover	284	0.41	0.01	0.58
Short-retraining mover	141	0.21	0.04	0.76
Untrained mover	146	0.14	0.05	0.82
Totals	1 144	0.39	0.02	0.59

Table A.7: 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
Incumbent - 3 years of experience	143	0.49	0.01	0.50
Incumbent - no experience	137	0.39	0.01	0.60
Long-retraining mover	278	0.51	0.01	0.48
Short-retraining mover	141	0.32	0.01	0.67
Untrained mover	136	0.30	0.04	0.65
Totals	1 112	0.46	0.02	0.53

Table A.8: Positive, negative and non-response callback, per profile, Plumbers

	Nb. applications	Positive callback	Negative callback	Non-response
Incumbent	277	0.54	0.01	0.45
Incumbent - 3 years of experience	139	0.50	0.01	0.50
Incumbent - no experience	137	0.30	0.03	0.67
Long-retraining mover	274	0.40	0.02	0.58
Short-retraining mover	146	0.18	0.04	0.78
Untrained mover	134	0.19	0.04	0.78
Totals	1 107	0.38	0.02	0.60

Table A.9: 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	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	0.1072	0.0120	0.0797	-0.1008	0.1275	0.0659
	(0.0877)	(0.0997)	(0.0669)	(0.0818)	(0.0993)	(0.1045)
Occupation indicators	✓	✓	✓	✓	✓	✓
Observations	942	922	961	915	938	947

Reference type: Untrained and short-retraining movers.
Additional controls: Candidate dummy, sending order of applications, commute time to firm, recent move indicated, firm size and productivity. All controls are interacted with profile category.