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ISSN 1651-1166

Vacancy referrals and broader job search: the role of spillovers among caseworkers *

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September 17, 2026

Abstract

This paper provides the first causal evidence of behavioral spillovers in public employment services (PES). Using rich Swedish administrative data from 2004–2018 and a difference-in-differences design exploiting caseworker moves across local PES offices, I show that caseworker’s broader vacancy referral behavior—vacancy referrals outside a job seeker’s stated preferences—responds strongly to the local work-practice styles. I also examine how these practice-environment shocks of the movers (caseworkers) affect their job seekers. Taken together, the evidence suggests that local referral practices and the surrounding organizational environment play an important role in shaping caseworker behavior, with consequences for job seekers’ reemployment prospects.

JEL Classification: J24, J64, J68, C21, J24, I38

Keywords: occupational mismatch, caseworkers, peer effects, job search, public employment services, active labor market programs, difference-in-differences

*I would like to thank Johan Vikström, Peter Fredriksson, Pierre Deschamps, Olof Rosenqvist, Oskar Nordström Skans, Lena Hensvik, Georg Graetz, Jonas Cederlöf, Martin Lundin, Andrei Groshkov, and Eva Mörk for their insightful comments and suggestions. This work has further benefited from discussions with members of the Uppsala Labor Group and participants at the CREST-IFAU Workshop

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1 Introduction

Job-search assistance (JSA) is perhaps the most efficient policy tool in reconnecting the unemployed with employment. Delivered through the caseworkers at the public employment service (PES) offices, JSA typically involves vacancy referrals¹, counseling, job suggestions, and career planning that are tailored to individual needs and shaped by caseworker discretion. There is strong empirical evidence supporting the effectiveness of JSA in increasing re-employment probabilities (Card et al., 2010; Cheung et al., 2025; Crépon et al., 2005; Van den Berg et al., 2014; Weber & Hofer, 2003). Consistent with this rationale, many developed countries expand spending on job-search assistance and public employment services during periods of rising unemployment.² Some recent studies have also examined the influence of caseworker attributes (Cederlöf et al., 2026), caseworker-job seeker interactions (Schiprowski, 2020), and referral mechanisms (Bollens & Cockx, 2017) that have proved to be very relevant for job seeker’s labor market outcomes. However, little is known about the factors that drive individual caseworker’s vacancy referral strategy or behavior and how these, in turn, affect the labor market prospects of job seekers.

Vacancy referrals constitute a core component of job-search assistance, serving as one of the most direct and effective tools through which caseworkers at public employment service (PES) offices facilitate job matching. Cheung et al. (2025) show that increased number of referrals significantly improves re-employment outcomes of the job seekers. In addition to the frequency of referrals, the type of referral may also be a key factor. Recent policies in many countries encourage job seekers to consider a wider set of occupations and opportunities beyond their previous occupations or narrow preferences, often termed as “broader referral”. This strategy aims to broaden job seekers’ search horizons to improve match quality and expedite re-employment, assuming that unemployed workers often misjudge their employment prospects (Van der Klaauw & Vethaak, 2022). Empirically, Belot et al. (2019; 2022) document that broader referrals improve labor market outcomes for underprivileged groups of job seekers. However, recent evidence reports mixed effects of broader referrals—ranging from muted to negative impacts on employment outcomes (Dhia et al., 2022; Van der Klaauw & Vethaak, 2022).

In this paper, I explore two under-researched questions related to JSA and vacancy referrals. Firstly, I investigate whether an individual caseworker’s vacancy referral behavior or strategy is influenced by the practice-environments at the local PES office. This inquiry is grounded in a broad literature on peer effects, which highlights how individuals are often shaped by the actions

¹A vacancy referral is defined as an instance in which a caseworker formally assigns or recommends a job seeker to a specific job opening with a particular employer.

²Appendix figure A1 shows the relationship between unemployment rates, and PES administrative and JSA expenditures using OECD country-year observations from 2005-2020. The figure indicates a positive correlation, consistent with countercyclical increases in job-search support related spending during periods of higher unemployment.

and social norms of those around them (Bandiera et al., 2009; Mas & Moretti, 2009; Sacerdote, 2001). While prior studies on active labor market programs (ALMPs) have focused extensively on the effectiveness of program participation for job seekers, no attention has been paid to within-office behavioral dynamics among caseworkers, specifically, how caseworkers adapt their work strategies in response to local practice-environments. This study exploits the variation in practice-environment from caseworkers moving between local offices to identify whether and how caseworker referral behavior adjusts to the local environment. To the best of my knowledge, this study provides the first causal evidence of local practice-environment driven behavioral spillovers among caseworkers.

Secondly, this paper examines how caseworker’s exposure to different broader referral environments affects their job seekers’ labor market outcomes through the changes of their own behavior. Unlike prior research (Belot et al., 2019, 2022; Dhia et al., 2022) that evaluates broader search behavior through algorithmic job suggestions or informational nudges, typically implemented on online platforms and often targeted at narrowly defined and highly disadvantaged groups such as individuals with disabilities or long unemployment duration, this study analyzes vacancy referrals that PES caseworkers routinely issue to job seekers as part of their standard services. I try to identify the causal effect of shifts in the broader referral environment on job seekers’ reemployment outcomes by exploiting within-caseworker variation before and after relocation within local PES offices. The findings offer new insights about the role of broader referral environment at local PES offices on job seekers’ reemployment prospects.

This study combines rich administrative data from the Swedish PES offices with matched employer–employee records, wage data, and demographic information from Statistics Sweden, covering 2004–2018. These data allow tracking of both caseworkers’ referral behavior and their job seekers’ labor market outcomes. The empirical strategy employs a difference-in-differences and event-study design, focusing on PES caseworkers who move between local offices. Variation in the “Leave-one-out” mean³ of broader referral behavior across origin and destination offices, defined as exposure or treatment to the caseworkers, identifies how differences in practice environments affect the “migrant” caseworker’s⁴ broader referral behavior. The key identifying assumption in this setting requires that no other factors except the practice-environment are affected or changed simultaneously with the move of caseworkers that are correlated with the changes in practice-environment and affect caseworkers’ referral strategy. I use a similar specification to estimate reduced-form effects comparing the labor market outcomes of a migrant caseworker’s new and previous job seekers. This approach enables a causal interpretation of how changes in caseworkers’ broader practice environments affect their clients’ reemployment

³The counterfactual office environment is the average broader referral rate among other caseworkers in the office—at the destination office before the move and at the origin office after the move.

⁴The term “migrant” caseworker refers to caseworkers who move between offices, not to those with migrant citizenship status.

prospects, thereby shedding light on the effectiveness of broader relative to narrower vacancy referral environments. The empirical design follows Molitor (2018) and Avdic et al. (2023), who study analogous spillovers among physicians.

I find evidence of strong spillover effects. Caseworkers who move to offices with a higher rate of broader referrals significantly increase their own broader referral behavior in response to the new practice environment. The results suggest that a one percentage point (pp) increase in the office’s broader referral rate leads to a 0.346 pp increase in the migrating caseworker’s broader referral rate. Event-study results further validate the presence of a behavioral discontinuity following relocation. A potential concern in estimating spillover effects is the reflection problem (Manski, 1993), which I address by defining the practice environment prior to relocation and control for exogenous peer characteristics to isolate genuine peer influences. Overall, the results are robust across all specifications, indicating that the estimated spillovers capture behavioral adaptation rather than correlated shocks or simultaneity. I also attempt to decompose the overall spillover effect into peer influence versus office-level or local labor market characteristics. This decomposition indicates that most of the estimated association remains after accounting for office fixed effects (0.284), suggesting an important role for peer-related factors, while a smaller component is associated with time-invariant office characteristics (0.062).

In terms of job seeker’s outcomes, I find that when a migrant caseworker is exposed to an office with a 10 pp higher broader referral intensity, the probability of exiting unemployment within 90 and 180 days decreases by 1.4 and 1.5 pp respectively. Event-study dynamics confirm that these discontinuities are both statistically significant and persistent. One possible explanation is that exposure to broader referral practices may induce job seekers to submit more applications across a wider range of vacancies, potentially reducing average application quality or match precision. If so, this could weaken the signaling value of individual applications to employers and reduce callback or hiring probabilities. This mechanism should, however, be viewed as a plausible interpretation rather than a directly established channel. More generally, the results suggest that changes in the referral practices to which caseworkers are exposed can translate into meaningful differences in job seekers’ reemployment outcomes. These estimates are robust to controlling for local labor-market-by-year fixed effects and remain stable after the inclusion of these controls. Using the full sample, I further compare migrant and non-migrant (stayer) caseworkers and find no statistically significant differences between movers and stayers.

This paper relates to several strands of literature. First, this paper contributes to the literature on peer effects and behavioral spillovers across institutional contexts. In health care, Molitor (2018) and Avdic et al. (2023) show that cardiologists adjust treatment styles after moving between hospitals, influenced by local practice norms. In labor, Ichino and Maggi (2000) document peer effects on shirking, while Sacerdote (2001) finds that randomly assigned college roommates affect academic and social outcomes. Åslund and Fredriksson (2009) further show

that ethnic peers' welfare use influences individual take-up under Sweden's refugee placement policy. Building on these studies, I provide the first causal evidence of behavioral spillovers among local PES caseworkers. By exploiting plausibly exogenous variation from caseworkers' transitions across local offices in Sweden, I show that exposure to new peer environments shifts individual broader referral behavior. This demonstrates that referral behavior is adaptable rather than predetermined, and highlights the influence of peer norms in shaping the delivery of public employment services.

Secondly, using rich administrative data with detailed caseworker and job seeker information, this study contributes to the literature on broader job search policies. Belot et al. (2019) show that algorithm-based job recommendations increase interview rates, particularly among the long-term unemployed, and Belot et al. (2022) find lasting employment and earnings gains. Both rely on small-scale experiments with limited external validity. In contrast, Dhia et al. (2022) find no effects of large-scale online recommendations, while Altmann et al. (2018) report modest gains from informational brochures concentrated among high-risk job seekers. The only study, to my knowledge, evaluating mandated broader search is Van der Klaauw and Vethaak (2022), who find that enforcement tied to vacancy referrals lowers job-finding rates. However, this paper adds nuance by examining broader search arising from institutional shifts in caseworker behavior and shows that when caseworkers move to offices with higher broader-referral intensity, their job seekers' exit probabilities decline, which suggests that indiscriminate broadening may hinder reemployment.

Thirdly, this paper relates to the literature on the role of caseworkers in shaping job seeker outcomes. Prior studies offer mixed evidence. Using Swiss data, Lechner and Smith (2007) find that caseworkers do not outperform algorithmic assignment of job seekers to ALMPs, whereas Cederlöf et al. (2026) show that caseworker characteristics affect job seekers' labor market performance. Likewise, Schiprowski (2020) and Van den Berg et al. (2014) find that more frequent meetings shorten unemployment spells. The present study extends this literature by documenting behavioral spillovers in caseworkers' broader referral strategies and their implications for job seeker outcomes, offering an organizational perspective on public employment service effectiveness.

Finally, this paper contributes to research on vacancy referrals, their channels and effectiveness. Cheung et al. (2025) show that referrals and individualized meetings are the main channels through which caseworkers affect unemployment duration, while Bollens and Cockx (2017) find that personalized referrals outperform automated ones. This study shifts the focus from the quantity, or mode of referral delivery, to the exposure to different vacancy referral environments.

The remainder of the paper is organized as follows. The next section provides institutional background on the Swedish Public Employment Service and caseworkers' broader referral behavior. The subsequent sections describe the data and sample selection, discuss caseworkers'

practice environments, and present the empirical framework. The main results and robustness checks are then presented, followed by an examination of job seekers' outcomes and heterogeneity. The final section concludes by summarizing the findings and discussing their implications.

2 Swedish Public Employment Service offices and caseworkers

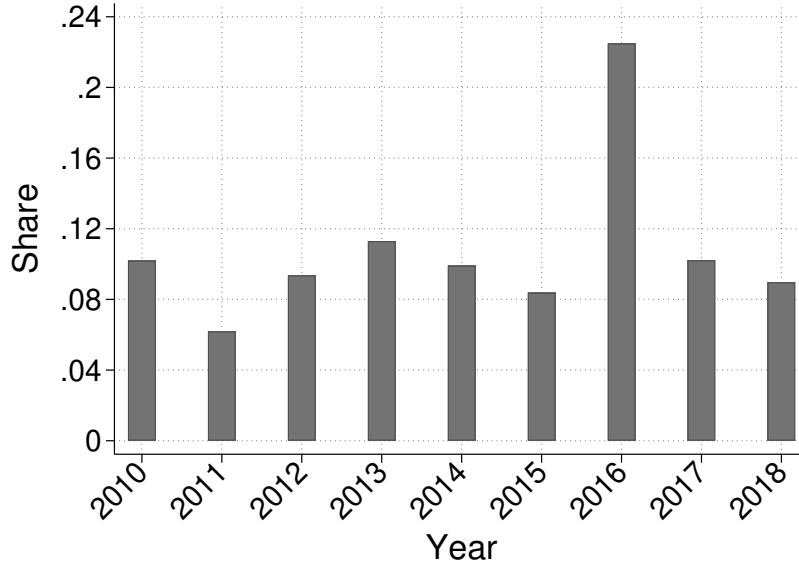
The Swedish Public Employment Service (PES, *Arbetsförmedlingen*) is a central institution in Sweden's labor market policy, tasked with reducing unemployment and supporting job seekers in their transition to work by ensuring efficient matching between job seekers and employers while addressing structural challenges such as skill mismatches, regional disparities, and the integration of under-represented groups, including migrants and individuals with disabilities. PES offers extensive services to job seekers (e.g., vacancy referral, career counseling, training programs, and financial support for skill development) and to employers, who benefit from recruitment assistance, hiring subsidies, and access to a large candidate database; notably, more than half of PES staff are caseworkers. Although guidelines and legislation frame service provision, caseworkers retain substantial discretion, a flexibility attributed to broad policy frameworks and outcome-focused performance evaluations rather than mandated strategies (Lagerström, 2011; D. Lundin, 2004). This autonomy allows them to tailor interventions to local labor market conditions and heterogeneous client needs. Sweden also imposes no standardized educational requirements for caseworkers, instead valuing diverse professional backgrounds, and local PES offices are encouraged to adapt their organizational practices to regional circumstances—for example, matching job seekers to caseworkers based on sector expertise or using neutral assignment rules such as date of birth to balance caseloads (M. Lundin & Thelander, 2012). These varied approaches underscore the foundational importance of caseworkers in implementing labor market policy and highlight the need to understand and strengthen the factors that enhance their effectiveness.

2.1 *Caseworker movement within Swedish PES*

Caseworker mobility within public employment systems presents a unique opportunity to examine how individual behaviors adapt to changing organizational environments. This geographic relocation of caseworkers across local offices can generate quasi-experimental variation in exposure to peer environment. Importantly, the localized nature of PES offices, each with potentially distinct referral tendencies and managerial styles, makes caseworker relocation a valuable source of identifying variation.

To identify caseworkers who relocate their job, I focus on those who move across two different offices. Moves are identified using office and caseworker identifiers. I treat caseworkers as movers who have worked at a single office in a specific year and who have not switched offices more than once during the entire sample period. Restricting the analysis to individuals with a single

Figure 1: Annual transition rate of caseworkers across offices



Notes: Figure 1 is drawn using the PES admin dataset. This figure shows the annual transition rate among caseworkers in Sweden for the period 2010-2018. This figure represents those caseworkers, who held at least 1 physical meeting with their job seekers at the office.

move sharpens identification of peer spillover effects. Multiple relocations expose individuals to varying peer environments over short periods, obscuring the influence of any specific practice environment. Repeated movers may also differ in unobserved traits (e.g., adaptability or network formation) that affect both mobility and responsiveness to peer norms. Focusing on one-time movers therefore enables cleaner attribution of spillover effects to a single peer environment rather than to selection-driven mobility patterns. Of the 11,352 unique caseworkers analyzed, 1,789 (15.76%) were identified as movers.

Figure 1 highlights the migration patterns of caseworkers working in Swedish public employment service offices during 2010-2018. It shows that the annual transition rate of caseworkers in Sweden. For most part of the last decade, the transition rate remains in the range of 8%-10%. However, there is a spike around 2016 when the transition of caseworker peaked to more than twenty percent. Most of the movement in this transition rate could be attributed to the gradual downsizing of local PES offices in Sweden during the sample period.

2.2 Broader referral behavior

In this study, broader referral behavior is defined by the extent to which the initial job suggestion or vacancy referral made by a caseworker falls outside the occupational preference informed by the job seeker during their registration at the PES. These preferences could be shaped by a combination of factors, including the job seeker's ideal or "dream" job, perceived employment

prospects, and alignment with prior experience or qualifications⁵. This measure captures instances where the caseworker recommends positions that do not align closely with the job seeker’s stated preferences. I track this broader vacancy referral behavior of individual caseworker over time and across different offices using the unique caseworker identification number. This unique identifier remains consistent throughout a caseworker’s tenure during the sample period. I also focus on the first referral, rather than alternative measures such as the average rate of broader referrals or probability of ever receiving a broader referral. While many factors might influence the referral behavior of caseworkers during a job seeker’s unemployment spell, focusing on the first referral helps to some extent in reducing concerns about endogeneity in the vacancy referral behavior of the caseworkers. Throughout this paper, the terms referral and broader referral are used interchangeably.

Understanding broader referral behavior is important from both a behavioral and policy perspective. These referrals can influence the quality of job matches, job seeker motivation, and ultimately labor market outcomes. While previous studies have shown that informational nudges or voluntary broadening of search can improve job outcomes (Belot et al., 2019, 2022) for selective job seekers but not for others (Dhia et al., 2022), mandatory broadening might be counter-productive for the job seekers (Van der Klaauw & Vethaak, 2022). Overall, the evidence on the effectiveness of broader vacancy referral remains limited. This paper provides new evidence on how caseworkers’ adoption of broader referral behavior—triggered by changes in their peer environment—affects job seekers’ employment outcomes in a context where vacancy referral is institutionalized. Here, the analysis contrasts the effect of highly broader practice-environment with less broad ones, rather than assessing the impact of broader referrals on their own.

3 Data and sample

For this study, I use different Swedish administrative datasets containing important demographic, education and employment history of the unemployed job seekers registered at the PES. I use the data from 2004-2018 as there is not much referral data prior to 2004; whereas, I do not have information beyond 2018. I use the population register Louise from Statistics Sweden that contains demographic information (e.g., age, gender etc.) and education (type and level). I also use the matched employer-employee data (RAMS) from Statistics Sweden to add information of earnings and employment status of the job seekers prior and after each unemployment spell. In this way, I am able to extract the rich employment history of each job seeker.

PES register data is used to construct unemployment spell data. The same register is also

⁵Appendix figure A2 examines whether job seekers’ stated preferences, at the PES, genuinely reflect their actual occupational preferences. To assess this, I predict the probability that each job seeker prefers a given occupation and then rank these predicted preferences. Approximately 60% of job seekers’ stated preferences fall within their top four predicted occupations, suggesting that the stated preferences largely capture their true occupational choices.

used to construct the vacancy referral dataset, which contains the actions of both job seekers and their assigned caseworkers for each vacancy referral and job suggestion. This dataset contains the vacancy identifier along with location of the vacancy, occupational code, type of vacancy, application deadlines, information about whether the job seeker applied to or not etc. To elicit the preference⁶ of the job seekers as well as referral behavior⁷ of the caseworkers, I use the information from the vacancy referral dataset. I also use meeting information from the PES registers at the PES to extract the caseloads (e.g., number of job seekers assigned to the caseworkers), frequency of vacancy referral and job suggestions per year, tenure of caseworkers (i.e., the number of years worked as caseworkers at the PES), the number of offices at which a caseworker worked at in a given year and most importantly, the point in time when a migrant caseworker switches office. The major outcome variables used in this study are: (i) probability of exiting unemployment from receiving the first referral within 90 and 180 days respectively, and (ii) log earnings in year $t + 1$ and $t + 2$ after the spell starts, or specifically the short-run future earnings. To map the local labor market within my sample dataset, I use the local labor market definition⁸ from Statistics Sweden.

The sample consists of all job seekers registered at the PES from 2004-2018. As stated earlier, I exclude caseworkers who switched offices more than once during their tenure. To enhance the precision of the empirical analysis, the sample is restricted to PES offices that employ at least three caseworkers within a given year. This restriction is motivated by the need to reduce measurement error in the construction of the leave-one-out mean of referral intensity, which serves as a proxy for average peer behavior within an office. All movers in the sample have worked at least 1 year in origin and destination offices respectively. The final dataset contains 626,248 unique unemployment spells (splitted between stayers and migrant caseworkers), 1,789 unique migrant caseworkers, and 9,563 unique stayers.

4 Practice-environment based on broader referral

4.1 *Practice-environment*

Building on the definition of broader referral behavior in the earlier section, the empirical analysis seeks to identify how migrant caseworkers adjust their own referral behavior in response to changes in their surrounding practice environment. I calculate the broader referral behavior for each caseworker at office-year level using a “leave-one-out” method that excludes their own job seekers. While the practice environment likely includes unobserved components, the

⁶Job seekers are allowed to state their four digit occupational preferences after the of registration at PES.

⁷By referral behavior, I mean both job suggestion and job referral towards a job seeker.

⁸In my sample, I fix the local labor market using the 2005 definition from Statistics Sweden. The local labor market mappings from Statistics Sweden are compiled on yearly basis; however, the mappings do not vary much across years.

leave-one-out measure provides a tractable proxy by eliminating the mechanical correlation between an individual’s behavior and the office-level average.⁹ This strategy allows for a cleaner estimation of the extent to which caseworkers internalize and respond to the referral norms of their new organizational setting. I define practice-environment of caseworker $n \in N$ in office $z \in Z$, where job seeker $m \in M_{zt}$ received a broader referral (as their first referral) in time period $t \in T$, as the ratio:

$$\Xi_{nzt} = \frac{\sum_{m \in M_{kzt}} \mathbb{1}(Broader_m = 1)}{M_{kzt}}, \quad \forall k \neq n \in N \quad (1)$$

where $M_{kzt} \subset M_{zt}$ is the subset comprising all job seekers other than those assigned to caseworker n . Hence, Ξ_{nzt} is caseworker n ’s exposure to the practice-environment with respect to the rate of sending out broader referral to the relevant job seekers in office z at time t . Next, I define the difference in these practice-environments between a migrating caseworker’s origin ($z_{Ori.n}$) and destination ($z_{Des.n}$) offices at a given point in time as:

$$\Delta_{nt} = \Xi_{z_{Des.n}t} - \Xi_{z_{Ori.n}t} \quad (2)$$

In essence, Δ_{nt} is the period-specific difference in “leave-one-out” shares between the offices where caseworker n worked before and after relocation. At each point in time, one of the two shares in equation (2) is counterfactual, defined as the peer exposure generated by caseworkers in the office where n is not currently employed. Together, equations (1) and (2) define caseworkers’ exposure to the practice environment over time. The difference in equation (2) provides the time-varying measure of this exposure.

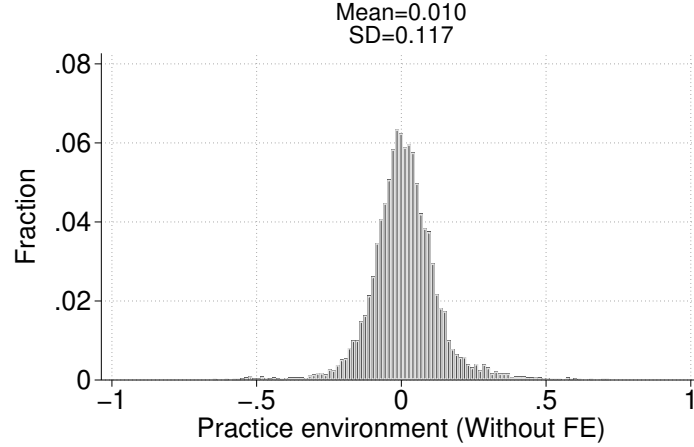
This rich administrative data sample generates substantial variation in exposure to different practice-environments, which are measured using the leave-one-out share of broader referrals at the office-year level.¹⁰ To illustrate how these environments change when caseworkers relocate, figure 2 shows the distribution of changes in broader referral intensity (Δ_{nt}). The distribution is centered around zero, indicating that movers are about equally likely to experience increases or decreases in referral intensity. Overall, the figure demonstrates ample variation in the changes in caseworker’s practice environments, which is crucial for identifying the causal effects of exposure to different levels of office norms on caseworker referral behavior and job seeker outcomes.

Figure 3, on the other hand, depicts the evolution of referral intensity, measured as the share of broader referrals, at different types of PES offices before and after a caseworker relocates. The analysis distinguishes moves from high- to low-referral offices (Panel 3a) and from low-

⁹I explore office-level practice-environment instead of regional variation in practice-environment for two important reasons: (i) the sample dataset can not identify the location of office; (ii) office-level practice environments enables more precise identification, as local office cultures and norms may vary meaningfully even within the same geographic area.

¹⁰Appendix figure A3 shows the distribution of practice-environments for all the migrant caseworkers in the sample dataset, which shows the variation in levels.

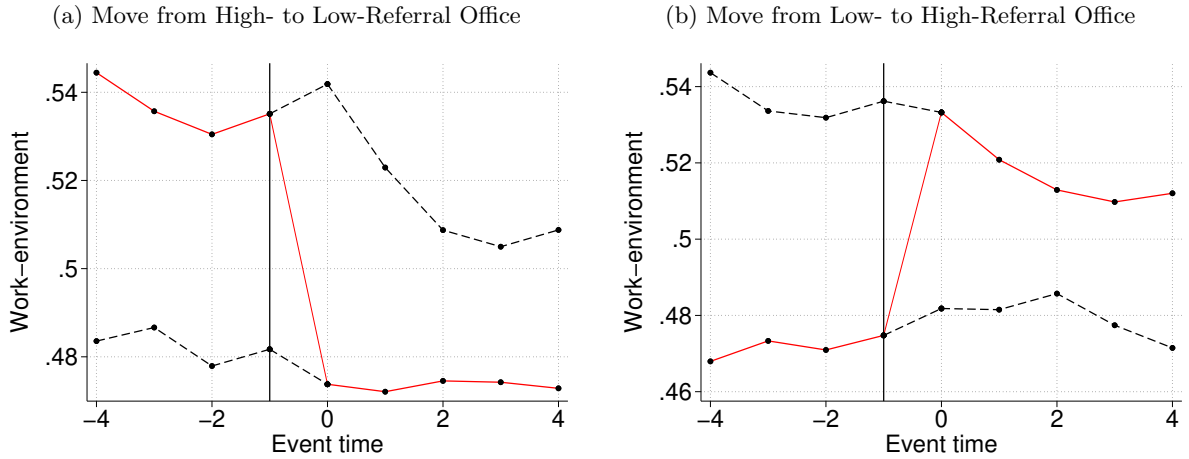
Figure 2: Time-Variant Change (Δ_{nt}) in Practice Environment for Migrating Caseworkers



Notes: Figure 2 shows the distribution of changes in practice environment for migrant caseworkers due to inter-office moves during 2004-2018, and it uses year-specific referral environments at the time of the move. Measures are constructed from leave-one-out broader referral rates.

to high-referral offices (Panel 3b). For each group, the solid lines plot the realized practice environment (the leave-one-out referral intensity at the office where the caseworker is located), while the dashed lines show the corresponding counterfactual trend in the origin or destination office.

Figure 3: Dynamics of Referral Intensity in Different Office Types



Notes: Figure 3 is based on sample data from 2004–2018. Solid lines show the realized office-level referral intensity; dashed lines show the counterfactual (origin or destination) intensity. Event time is represented in the horizontal axis and is centered on the relocation year.

Both panels reveal a clear pattern: despite some year-to-year variation, offices maintain their relative ranking in referral intensity. High-referral offices remain high-referral after receiving new staff, and low-referral offices remain low-referral, indicating that referral culture is a persistent institutional characteristic rather than one that shifts quickly with staff mobility. Given the temporal fluctuations in office styles, it is important to account for deviations in referral intensity

(Δ_{nt}) within the empirical strategy. Including Δ_{nt} as a regressor allows the model to absorb linear divergence in office-level practices that might otherwise confound treatment effects, ensuring that observed behavioral changes are not spuriously attributed to independent shifts in local norms. Overall, figure 3 demonstrates that office environments evolve but remain relatively stable in their relative intensity. This persistence motivates focusing on changes in caseworker exposure to distinct referral cultures and incorporating time-varying adjustments to isolate their causal effects.

5 Econometric framework and identification

The empirical strategy in this paper aims to quantify the impact of caseworkers' practice-environment on their individual decision making styles in the context of sending out broader vacancy referral to their respective job seekers. The approach exploits plausibly exogenous variation arising from the mobility of migrant caseworkers across offices and relies on a difference-in-differences and event-study framework. The identification leverages variation in the practice environment across origin and destination offices to estimate the causal effect of changes in caseworkers' local environments on their own treatment behavior following a move. The major identifying assumption is that no other factors except the practice-environment are affected or changed simultaneously with the move of caseworkers that are correlated with the changes in practice-environment and affects caseworkers' treatment styles. A similar econometric framework is also employed to examine the effect of the practice environment on job seekers' subsequent labor market outcomes.

5.1 *Spillover effects among migrant caseworkers*

The empirical specification in this paper is based on the unemployment spell-level difference-in-differences (DiD) framework for job seeker $m \in M$, assigned to caseworker $n \in N$ at time $t \in T$ that is given in the following equation:

$$y_{mnt} = \beta \Delta_{nt} + \phi(\Delta_{nt} \times \text{Post}_t) + \Psi'_{mnt} \Omega + \zeta_n + \zeta_t + \epsilon_{mnt} \quad (3)$$

where the outcome y_{mnt} is a binary variable that takes 1 if a job seeker receives a broader referral and 0 otherwise. The dummy, Post_t , is an indicator variable that assumes 1 for all subsequent time periods after the caseworker n 's migration to a new office, i.e., $\text{Post}_t = \mathbb{1}_{t \geq t_0}$ where t_0 is the time when the migration takes place. This baseline model also includes caseworker and referral year fixed effects (ζ_n and ζ_t) along with controls for job seeker characteristics, Ψ_{mnt} . The characteristic controls and fixed effects are used to adjust for the observed and unobserved heterogeneity across job seekers, caseworkers and time. Δ_{nt} is a continuous variable in the range $[-1,1]$ that captures the time-variant empirical variations in the practice-environment of the

caseworkers (with respect to the average share of sending out broader referrals to the job seekers registered at those offices at time t) after their relocation. The major parameter of interest is the ϕ in the baseline DiD¹¹ equation (3), which captures the average change in a caseworker’s broader referral behavior after relocation relative to before, driven by differences in practice environments between origin and destination offices. In effect, ϕ measures the percentage-point change in a migrating caseworker’s broader referral behavior associated with a one-percentage-point shift in the practice environment. I also include Δ_{nt} as a regressor to control for linear deviations in the relative trend between origin and destination practice-environments over time (see figure 3). In other words, it as a control for linear deviations in the common trend as in a standard DiD analysis.

To study the dynamics of the migrant caseworkers’ behavioral responses due to the difference in the practice-environment, I expand the baseline framework into an event-study specification where the $Post_t$ dummy is replaced with period-specific indicator. as follows:

$$y_{mnt} = \beta \Delta_{nt} + \sum_{s=-T'}^{T'} \mathbb{1}(s = t') [\alpha_{t'} + \phi_{t'} \Delta_{nt'}] + \Psi'_{mnt} \Omega + \zeta_n + \zeta_t + \epsilon_{mnt} \quad (4)$$

This dynamic pattern would help to verify the parallel trend assumption. The period-specific indicator in equations (4) is the “event-time” t' , where t' is the time-index relative to the migration for caseworker n . The above equation is expected to capture the migrant caseworker’s behavior in response to the changes in practice-environment Δ_{nt} over time. This is estimated by interacting the change in practice-environment (Δ_{nt}) with event time dummies $\mathbb{1}(s = t')$.

In addition to the baseline specification, I include *local labor market*¹² fixed effects to account for regional heterogeneity in job opportunities. These controls absorb structural differences across areas that may influence caseworkers’ referral decisions. To further strengthen identification, I add local labor market–year fixed effects, which capture time-varying regional shocks (e.g., changes in unemployment or industry composition) that could otherwise confound estimated effects. Across all specifications, standard errors are clustered at the caseworker level to address serial correlation and unobserved individual heterogeneity.

5.2 Robustness analysis

One of the major challenges in estimating spillover or peer effects is the reflection problem (Manski, 1993), which is the empirical difficulty in distinguishing whether observed similarities in group behavior are due to individuals influencing each other (endogenous peer effects), due to common exposure to peer characteristics (exogenous effects), or driven by shared environments

¹¹Similarly, the major parameter of interest in the even-study specification is $\phi_{t'}$.

¹²According to Statistics Sweden (SCB), a *local labor market* is a functional area centered on one or more municipalities that are largely self-sufficient in employment. A municipality qualifies as an independent local center if at least 80 percent of its employed residents work within the municipality and no external commuting flow exceeds 7.5 percent (Hedin & Tegsjö, 2006).

or selection into similar groups (correlated effects). However, the presence of simultaneity, where individuals both influence and are influenced by their peers, creates mechanical co-movement in outcomes that cannot be disentangled without further assumptions or structure. This limitation is especially pertinent in workplace settings, where employees are jointly exposed to organizational norms, supervision, and client characteristics. To resolve the reflection problem, I use the following identification strategies to alleviate the risk of conflating causality with correlation.

In the first specification, I use pre-move differences between origin and destination offices as a time-invariant measure. This precludes the simultaneity bias that arises when practice-environments are measured after the mover has joined the destination office. By anchoring the treatment variable to office practices before any possible influence by the mover, this strategy mimics the logic of an instrumental variable approach, using variation plausibly exogenous to the mover’s own behavior. A second strategy evaluates whether spillovers are attributable to observable exogenous characteristics of the new peer group rather than their behavior. In this case, I include differences in average tenure of peers at the destination and origin offices. If more experienced peers influence behavior differently, differences in tenure could explain part of the spillover effect.

I also compare the referral behavior of migrant and non-migrant (stayer) caseworkers, following Molitor (2018). This specification includes origin and destination office fixed effects along with year fixed effects and is estimated on the full sample of movers and stayers.¹³ This approach offers two advantages: (i) first, it expands the estimation sample, increasing statistical power, and (ii) second, it enables a direct comparison between movers and stayers to test for systematic differences in their respective referral intensities.¹⁴

5.3 *Decomposition of practice-environment effect*

As pointed earlier, the baseline DiD specification in this study captures the change in individual caseworker behavior due to changes in overall practice-environment after the relocation. This practice-environment could be a combined effect of the peers with whom the caseworkers work, and the office-specific elements that may also include local labor market factors. Assuming that office-specific components are constant over time, we further examine the extent to which the estimated practice-environment effect is associated with peer-related rather than time-invariant office-specific factors by adding office fixed effects to the baseline specification. The inclusion of office fixed effects absorbs persistent unobserved differences across offices. Consequently, the remaining estimate captures variation that is not explained by time-invariant office characteristics and is therefore consistent with a peer-related component of the practice environment. The

¹³For stayers, the origin and destination office are defined as their current office. Their event time and change in practice environment (Δ_{nt}) are set to -1 and 0 , respectively.

¹⁴This specification does not capture the referral behavior of individual caseworkers, as it reflects only the average behavior across groups defined by origin–destination office pairs.

difference between the baseline estimate and the estimate obtained after controlling for office fixed effects can, correspondingly, be viewed as an indicative measure of the component associated with time-invariant office-specific factors. This decomposition should not be interpreted as a sharp separation between peer and office influences, since the two may be intertwined.

5.4 *Estimating job seeker's outcomes*

I use similar specifications to estimate job seekers' outcomes when their caseworkers are exposed to different offices with regard to broader referral intensity, and the reduced form specification is below:

$$y_{mnt} = \beta \Delta_{nt} + \phi(\Delta_{nt} \times \text{Post}_t) + \Psi'_{mnt} \Omega + \zeta_n + \zeta_t + \zeta_{llm \times t} + \epsilon_{mnt} \quad (5)$$

where y_{mnt} is the labor market outcomes of job seeker m assigned to caseworker n at time t . In this paper, two broad types of job seeker outcomes have been explored; one is probability of exit from unemployment spell (within 90 and 180 days) and the other is future earnings up to period $t + 2$. Δ_{nt} is the time-variant changes in the migrant caseworker's practice-environment. The Post_t is an indicator variable that assumes 1 for all subsequent time periods after the caseworker n 's migration to a new office, i.e., $\text{Post}_t = \mathbb{1}_{t \geq t_0}$ where t_0 is the time when the migration takes place. Similar to the spillover estimation specification in equation 3, this specification also includes caseworker and referral year fixed effects (ζ_n and ζ_t) along with controls for job seeker characteristics Ψ_{mnt} . The job seeker's outcome model also includes local labor market by year fixed effects ($\zeta_{llm \times t}$) to account for potential contemporaneous shifts in local economic conditions. The characteristic controls and fixed effects are used to adjust for the observed and unobserved heterogeneity across job seekers, caseworkers and time.

To assess whether job seekers are systematically sorted across caseworkers, I conduct a placebo test by regressing predicted outcomes using a similar specification as in equation 5. Here, we do not control for the job seeker characteristics. Because these predicted outcomes are constructed from pre-determined characteristics, they should remain unaffected by contemporaneous referral practices for the validity of the identification. Therefore, finding no systematic relationship between the placebo outcomes and variation in practice environments would support the assumption that job seekers are not non-randomly sorted across caseworkers.

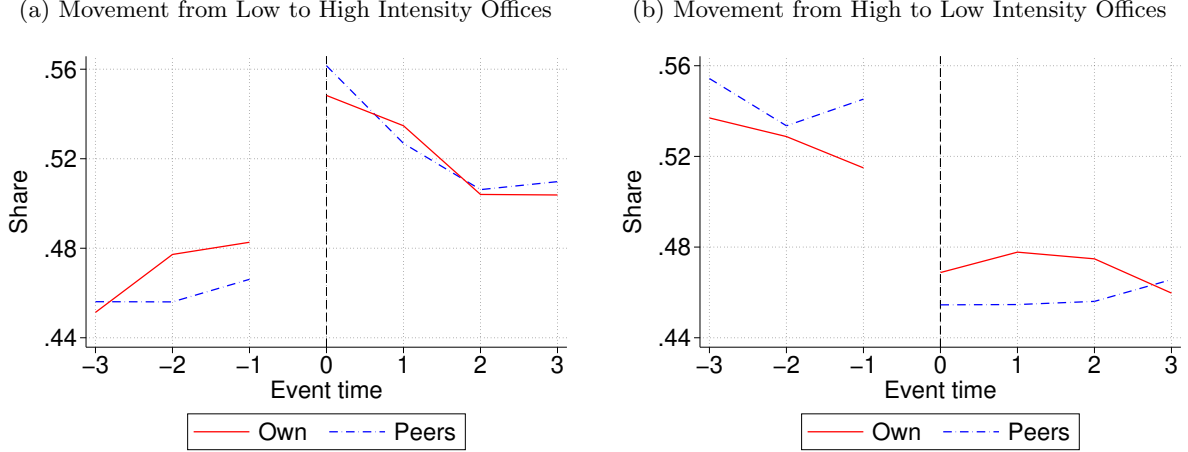
6 Do caseworkers change behavior upon changing offices

Figure 4 illustrates the raw association between a migrant caseworker's average referral behavior and that of their peers.¹⁵ Figure 4a displays how a migrant caseworker's referral behavior

¹⁵Peers before event time 0 belong to the origin office, while those from event time 1 onward belong to the destination office. "Own share" refers to the average broader referral rate of the migrant caseworker, whereas "peer share" is calculated as the leave-one-out mean of the broader referral rate for each caseworker.

adjusts when moving from a low-intensity to a high-intensity office in terms of sending broader referrals. Conversely, figure 4b illustrates the adjustment when transitioning from a high- to a low-intensity office. Both panels indicate that caseworkers' referral behaviors shift following relocation and tend to align with the average behavioral norm of the destination office.

Figure 4: Co-movement of Individual Work-Style with Peers



Notes: This figure is based on sample data from 2004–2018. Panel 4a shows how an individual caseworker's referral behavior co-moves with that of their peers when transitioning from low- to high-intensity offices. Panel 4b presents the same co-movement pattern for caseworkers relocating from high- to low-intensity offices.

Table 1 shows regression estimates of spillover effects using equation 3. Column (1) reports the baseline specification, which includes only year and caseworker fixed effects. The results indicate that a 1 pp increase in the broader referral intensity of an office leads to a 0.346 pp increase in the individual caseworker's broader referral rate following relocation. This specification exploits within-caseworker variation over time, comparing referral behavior before and after a move.

Table 1: DiD regression estimates using time-variant Δ_{nt}

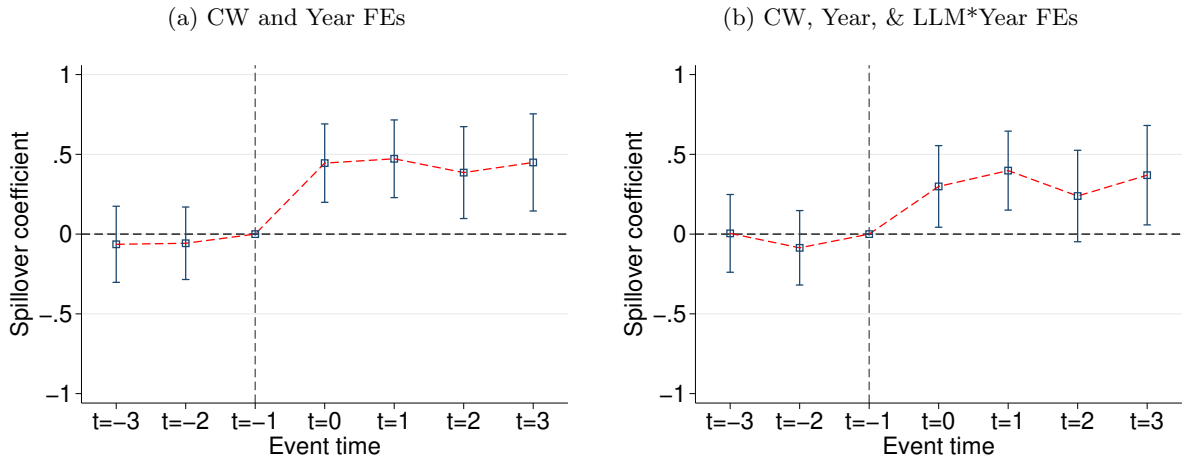
	(1)	(2)	(3)
Spillover coefficient (ϕ)	0.346*** (0.058)	0.291*** (0.059)	0.261*** (0.062)
Covariates	✓	✓	✓
Year FE	✓	✓	✓
Caseworker FE	✓	✓	✓
Local Labor Market FE	×	✓	×
Local Labor Market $\times$ Year FE	×	×	✓
Observations	115,785	114,483	114,385
R-squared	0.056	0.059	0.068

Notes: This table presents difference-in-differences estimates of the change in a caseworker's broader referral behavior across a move as a function of the time-variant change in the practice environment based on sample data from 2004-2018. Each column presents results from a separate regression. Columns are estimated over spell-level observations limited to migrant caseworkers only. The change in practice environment is defined at the office-year level. Each regression includes the same set of covariates (job seeker characteristics) and varying sets of fixed effects as shown. Standard errors are clustered at the caseworker level and shown in parentheses. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

However, one potential concern with the baseline specification is that unobserved spatial

characteristics of the destination office, such as local economic conditions or institutional norms, may independently influence referral behavior. To address this, column (2) adds local labor market fixed effects, and the estimated spillover effect remains sizable at 0.291. Column (3) further allows local labor markets to evolve by including local labor market–year fixed effects, capturing time-varying regional shocks. The coefficient remains substantial, with a 1 pp change in the broader environment associated with a 0.261 pp change in individual behavior. Collectively, the findings indicate that caseworkers adjust their work styles to align with the prevailing practices of their colleagues and, potentially, with managerial expectations when exposed to a new practice environment. Such adaptation, consistent with theories of peer influence and social conformity, implies that professional behavior is shaped not solely by fixed individual preferences or autonomous judgment, but also by locally embedded normative pressures within organizational contexts. Moreover, a larger spillover coefficient also indicates that newly arrived caseworkers’ behavior are more consistent with the prevailing norms of their destination office.

Figure 5: Dynamics of caseworker’s referral behavior using time-variant Δ_{nt}



Notes: This figure is based on the sample data for years 2004–2018. This figure shows the event-study graph of individual caseworker’s behavioral response due to changes in practice-environment. Panel 5a shows the response with time-variant changes in practice-environment using caseworker and year fixed effects. Standard errors are clustered at the caseworker level. Panel 5b additionally controls for interacted local labor market and year fixed effects.

The resulting DiD estimate from table 1 are also supported by the discontinuity observed in the post-relocation period of the event-study graph in each panel of figure 5. This event-study figure compares two specifications, with each dot representing an estimated period-specific spillover coefficient ϕ_{it} and vertical bars showing 90% confidence intervals. The dashed vertical line marks the event year in which caseworkers move to a new office. The dataset is unbalanced in terms of caseworkers, and ϕ_{-1} is normalized to zero as coefficients are identified relative to this reference period. The estimates show no meaningful pre-trends: coefficients in the years preceding relocation do not differ from zero, indicating no anticipatory adjustments in referral behavior. In the baseline specification (panel 5a), the relocation year exhibits a

sharp and statistically significant jump in $\phi_{t'}$, followed by persistently higher coefficients. This pattern suggests that caseworkers quickly and durably adjust their broader referral behavior to the practice environment of the destination office. The persistence of post-move effects also indicates that these responses are unlikely to be driven by slow-moving mechanisms such as skill accumulation or learning (Molitor, 2018).

Table 2: Robustness of the spillover coefficient

	Pre-move (Δ_n)		Δ in Peer Tenure		(5) Movers vs. non-movers
	(1) Baseline	(2) Alternative	(3) Baseline	(4) Alternative	
Spillover coeff. (ϕ)	0.438*** (0.095)	0.257** (0.104)	0.443*** (0.095)	0.265** (0.104)	0.407*** (0.050)
Changes in peer tenure			-0.007* (0.004)	-0.006* (0.004)	
Mover dummy					0.003 (0.004)
Covariates	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Caseworker FE	✓	✓	✓	✓	×
Local Labor Market $\times$ Year FE	×	✓	×	✓	×
Origin office FE	×	×	×	×	✓
Destination office FE	×	×	×	×	✓
Observations	112,713	111,324	115,870	114,470	626,248
R-squared	0.055	0.068	0.056	0.068	0.027

Notes: The table presents the difference-in-differences estimates based on the sample data from 2004-2018. Columns (1)–(2) use pre-move, time-invariant office practices to avoid simultaneity. Columns (3)–(4) additionally control for differences in average peer tenure across offices. Column (5) compares movers and non-movers. All regressions include job seeker covariates and standard errors clustered at the caseworker level. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

To address the reflection problem and isolate genuine peer influences from simultaneity and exogenous shocks from peers, I re-estimate the model, in column 1 and 2 of table 2, using time-invariant practice-environment constructed from pre-move differences between origin and destination offices. Because these office-level practices are defined prior to the mover’s arrival, this specification avoids contemporaneous feedback and relies solely on variation plausibly exogenous to the caseworker’s own behavior. The results show consistently positive and statistically significant spillover effects. Using pre-move practices, the estimated coefficients range from 0.438 to 0.257 across specifications, indicating that exposure to existing norms in the destination office has a meaningful influence on caseworker behavior and the findings persist even after controlling for local labor market shocks through LLM-by-year fixed effects.

Column 3 and 4 of table 2 report estimates that additionally control for differences in peer experience between origin and destination offices. The rationale is that if more experienced peers exert differential influence, variation in average peer tenure could account for part of the observed spillover. However, the coefficient on peer-tenure differences is extremely small and close to zero, and the spillover estimate remains stable and statistically significant. This robustness indicates that the spillover effects persist even after accounting for observable differences in

peer characteristics, reinforcing the interpretation that the results reflect genuine behavioral adaptation rather than correlated traits. Next, I examine whether migrant and non-migrant caseworkers are systematically different in their broader referral decisions. Column 5 of table 2 compares broader referral behavior of movers and stayers within the same origin and destination office pairs within a given year. The coefficient of mover dummy is small and statistically insignificant, and the spillover coefficient remains strongly positive. This indicates that movers and stayers behave similarly when exposed to comparable office environments, providing evidence against systematic sorting by caseworker type. I further assess whether the two groups differ along other observable work-related dimensions, including referral frequency, meeting intensity, and caseload size. Appendix table A1 shows no systematic differences within office-year cells, indicating that movers are not selectively sorted on key aspects of their work practices. Together, these findings strengthen the validity of the causal interpretation by ruling out sorting on observable caseworker or client characteristics. ¹⁶

6.1 Heterogeneity in spillovers

Table 3: Heterogeneity of spillover effects

	Transition type		Caseworker experience	
	(1) Low→High	(2) High→Low	(3) High exp.	(4) Low exp.
Spillover coeff. (ϕ)	0.309*** (0.082)	0.294*** (0.084)	0.374*** (0.070)	0.286*** (0.102)
Covariates	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Caseworker FE	✓	✓	✓	✓
Observations	59,161	56,624	72,578	43,207
R-squared	0.058	0.054	0.050	0.067

Notes: This table reports difference-in-differences (DiD) estimates using a time-variant measure of changes in the referral environment (Δ_{nt}) based on the sample data from 2004-2018. Columns (1)–(2) report results by transition type (low→high and high→low offices), and columns (3)–(4) by caseworker experience level (above- and below-median tenure). All regressions include year and caseworker fixed effects and control for job seeker characteristics. Standard errors are clustered at the caseworker level (in parentheses). Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

I examine heterogeneity by direction of transition (low→high vs. high→low) and caseworker experience. The estimates reported in column (1)-(2) of table 3 show that the magnitude and significance of the spillover coefficient are highly comparable across these two groups. This indicates that behavioral adjustments are not asymmetric: caseworkers tend to align their referral behavior with prevailing local norms regardless of whether they move into more or less intensive referral environments. The absence of directional asymmetry suggests that adaptation occurs broadly and consistently, reflecting an internalization of institutional norms rather than one-sided behavioral shifts. Finally, the results in column (3)-(4) also reveal no

¹⁶For appendix table A1, I run the following simple regression using caseworker-year level sample data:

$$movers_dummy_n = \alpha + \Phi'_{nt}\beta + \zeta_{origin\ office} + \zeta_{destination\ office} + \zeta_t + \epsilon_{nt} \quad (6)$$

where Φ'_{nt} denotes the matrix of observable caseworker traits. I also control for origin office, destination office and year fixed effects to identify whether movers and stayers at the same office are different along these characteristics.

significant difference between caseworkers having different levels of experience. Both high- and low-experience caseworkers exhibit statistically significant and similarly sized spillover effects, implying that tenure does not affect the extent of behavioral adaptation, a result that is consistent with the estimates reported in column 3-4 of table 2. Taken together, these findings demonstrate that the behavioral spillover effects are stable, symmetric, and insensitive to specification choices, underscoring the robustness and generality of the estimated influence of the referral environment on individual caseworker behavior.

6.2 Decomposing the spillover effects

To clarify the sources of the behavioral spillovers identified in the baseline specification, I examine the extent to which the estimated effect is associated with peer-related versus office-specific factors. The baseline DiD estimates capture changes in referral behavior following a move, but the aggregate practice-environment measure may reflect both peer-group influences and persistent institutional or spatial characteristics of the office. I therefore augment the baseline specification with office fixed effects, which absorb time-invariant differences across offices, such as persistent managerial practices, organizational routines, or structural constraints. The remaining estimate is identified from variation that is not explained by these time-invariant office characteristics and can therefore be interpreted as being consistent with a peer-related component of the practice environment. The difference between the baseline estimate and the estimate obtained after including office fixed effects provides an indicative measure of the component associated with persistent office-specific factors. This decomposition should not be interpreted as a sharp separation between peer and office influences, since these dimensions may be intertwined and may also vary over time.

Table 4: Decomposition of overall spillover effects using time-variant Δ_{nt}

	(1)	(2)
Spillover coefficient (ϕ)	0.346*** (0.058)	0.284*** (0.070)
Covariates	✓	✓
Year FE	✓	✓
Caseworker FE	✓	✓
Office FE	×	✓
Observations	115,785	115,781
R-squared	0.056	0.059

Notes: This table presents a decomposition of the spillover effects using a time-variant measure of the practice environment (Δ_{nt}) based on the sample data from 2004-2018. Column (1) corresponds to the baseline specification including year and caseworker fixed effects. Column (2) adds office fixed effects to isolate peer-group-specific spillovers by removing time-invariant office-level heterogeneity. All regressions are limited to migrant caseworkers and include covariates capturing job seeker characteristics. Standard errors, clustered at the caseworker level, are reported in parentheses. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 presents the results. Column (1) reports the baseline spillover estimate of 0.346 using the time-varying measure of changes in the practice environment. When office fixed effects are

added in column (2), the coefficient declines to 0.284. This reduction is consistent with part of the baseline estimate reflecting persistent office-specific factors. At the same time, the fact that roughly four-fifths of the estimated effect remains after controlling for office fixed effects suggests an important role for peer-related influences. The remaining one-fifth can be viewed as an indicative measure of the component associated with time-invariant institutional characteristics.

This pattern stands in contrast to settings such as healthcare, where institutional resources and infrastructure play a central role in shaping treatment behavior (e.g., Molitor 2018; Avdic et al. 2023). In the context of employment services, the relatively modest component associated with time-invariant office characteristics suggests that persistent physical or administrative features of the office are unlikely to account for most of the estimated behavioral response. At the same time, the sizeable component that remains after controlling for office fixed effects is consistent with an important role for peer-related influences within the local work environment. Such influences may operate through social learning, information sharing, or adaptation to prevailing practices among coworkers. The decomposition therefore supports the role of interpersonal and peer-related factors for understanding caseworker behavior.

7 Effects on Job Seeker Outcomes

This section examines whether behavioral spillovers among migrant caseworkers translate into measurable labor market consequences for the job seekers they serve. The analysis focuses on two outcome dimensions: (i) unemployment exit probabilities (within 90 and 180 days), and (ii) post-unemployment earnings up to two years after reemployment. These outcomes could serve as meaningful indicators of the effectiveness of job placement strategies.

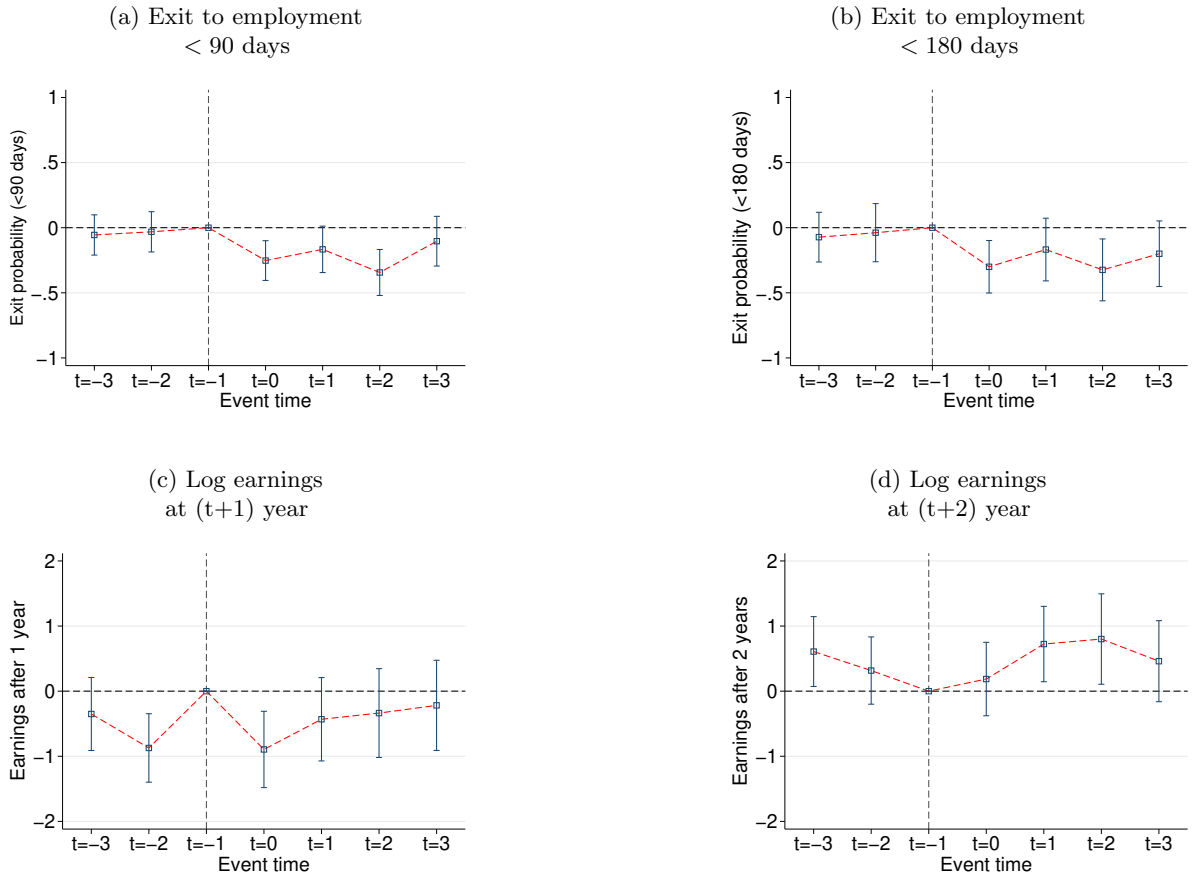
Table 5: Effect of Broader Referral Environment on Job Seekers’ Actual and Predicted Outcomes

	Actual Outcomes				Predicted Outcomes	
	(1) Unemp. dur. < 90 days	(2) Unemp. dur. < 180 days	(3) Earnings at $t+1$	(4) Earnings at $t+2$	(5) Unemp. dur. < 90 days	(6) Unemp. dur. < 180 days
Change in practice-env. (Δ_{nt})	-0.138** (0.055)	-0.150** (0.066)	-0.173 (0.172)	-0.046 (0.147)	-0.003 (0.003)	0.000 (0.008)
Covariates	✓	✓	✓	✓	×	×
Year FE	✓	✓	✓	✓	✓	✓
Caseworker FE	✓	✓	✓	✓	✓	✓
Local Labor Market $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	114,385	114,385	76,129	76,105	114,385	114,385
R-squared	0.074	0.107	0.143	0.149	0.017	0.026

Notes: This table presents difference-in-difference estimates of changes in unemployment outcomes related to broader referrals based on the sample data from 2004-2018. “Change in practice-environment (Δ_{nt})” refers to the effect of the changes in the migrant caseworker’s broader referral environment on their job seekers’ unemployment exit probabilities (columns 1–2), future log earnings (columns 3–4), and a placebo duration outcome based on predicted probabilities of exit (columns 5–6). Each column is estimated on a movers-only sample using spell-level data. All specifications include year, caseworker, and local labor market-by-year fixed effects. All columns excluding the predicted outcomes (columns 5–6) control for job seekers’ characteristics. Standard errors are clustered at the caseworker level and shown in parentheses. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5 presents the estimated effects of exposure to broader referral environments on unemployment exit probabilities. The results show that a 10 pp increase in a caseworker’s exposure to broader referrals reduces the likelihood of her job seeker’s unemployment exit within 90 days by approximately 1.4 pp, and within 180 days by roughly 1.5 pp respectively. Relative to the corresponding mean exit probabilities of 0.234 and 0.420, these estimates represent reductions of approximately 5.90 percent and 3.57 percent, respectively. Both effects are statistically significant at the 5 percent level. The magnitude and direction of these estimates suggest that when caseworkers are exposed to more broad referral offices, the matching process of their job-seekers becomes less effective.

Figure 6: Changes in practice-environment for caseworkers (Δ_n) and job seekers’ outcomes



Notes: This figure is based on the sample data for years 2004–2018. This figure shows the the event-study graph of job seeker’s duration and earnings outcomes in response to changes in caseworker’s practice-environment. All panels show the responses with time-variant changes in practice-environment using caseworker, year, and interacted local labor market and year fixed effects. Standard errors are clustered at the caseworker level.

One plausible explanation is that exposure to a broader-referral environment induces case-workers to adapt their referral behavior toward the prevailing practices at the new office. This greater use of broader referrals may, in turn, increase the number or scope of applications submitted by their job seekers while potentially reducing job–person fit, which could contribute to slower exits from unemployment. The results for post-unemployment earnings point in a similar

direction, although they are estimated less precisely. In particular, the coefficients for earnings at $t + 1$ and $t + 2$ are statistically insignificant. The dynamic pattern of these effects, illustrated in figure 6, further supports this interpretation. Following the move, exit probabilities decline persistently, indicating that the behavioral adjustment of caseworkers to new peer environments has lasting implications for client outcomes. The parallel pre-trends reinforce the validity of the identification strategy. Overall, the findings imply that adaptation of caseworkers to a high-intensity broader referral environment may inadvertently undermine placement effectiveness in the short run. In this setting, exposure to a broader-referral environment may lead caseworkers to adopt broader referral practices at the new office, which could increase search inefficiency if job seekers are directed toward vacancies that are less well aligned with their qualifications, preferences, or other constraints.

One key concern in interpreting these results is potential selection bias in the job seekers assigned to migrant caseworkers before and after their move. If caseworkers systematically transition between offices serving different client populations (e.g., those with higher or lower employability), the observed outcome changes could reflect differences in job seeker characteristics rather than true behavioral effects. To address this concern, a placebo analysis was conducted using predicted exit probabilities, as estimated from a model based solely on observable pre-treatment characteristics (e.g., age, education, work history, prior unemployment, and demographics) of the job seekers. These predicted outcomes capture job seekers' baseline employability independent of caseworker behavior. As shown in table 5 (column 5 and 6), the estimated coefficients on the key treatment variable are small and statistically insignificant across all specifications, indicating the pool of job seekers are similar across origin- and destination-offices.

Another potential concern is the channel of effects. One might worry that changes in the practice environment may simultaneously induce changes in other observable aspects of caseworkers' behavior that are related to their tasks. To examine this, I estimate a simple model regressing the change in the practice environment (Δ_{nt}) on several observable caseworker-level characteristics¹⁷: the number of referrals per caseworker per year, the number of job seekers assigned to each caseworker per year, and the average number of meetings per job seeker per year. The results, shown in appendix table A2, indicate that other caseworker functions at the PES office are not associated with the changes in practice-environment. This finding suggests that the primary channel through which job seekers are influenced might be the broader referral environment itself, rather than changes in the frequency of referrals, the intensity of interactions with job seekers, or the overall caseload of the caseworkers.

¹⁷For this, I run the following regression using caseworker-year level data on movers sample:

$$\Delta_{nt} = \alpha + \Phi'_{nt}\beta + \zeta_n + \zeta_t + \epsilon_{nt} \quad (7)$$

where Φ'_{nt} denotes the matrix of observable caseworker traits. I also control for caseworker and year fixed effects.

7.1 Heterogeneity in job seeker's outcomes

To examine whether the effects of broader referral environments vary across job-seeker characteristics, I estimate pooled difference-in-differences specifications in which the treatment effect is interacted with indicators for gender, age, and predicted unemployment duration. Table 6 reports the resulting subgroup-specific estimates for unemployment exit probabilities and post-unemployment earnings up to two years after reemployment. Panels A–B present the estimates by gender, Panels C–D by age group, and Panels E–F by predicted unemployment duration.

Table 6: Heterogeneity in job seeker outcomes by gender, age, and predicted duration

	Pr(Exit < 90 days)	Pr(Exit < 180 days)	Log(Earnings $t+1$)	Log(Earnings $t+2$)
Panel A: Males				
Change in practice-env. (Δ_{nt}) $\times$ Post-move $\times$ Males	-0.091 (0.062)	-0.122* (0.070)	-0.099 (0.200)	0.095 (0.172)
Panel B: Females				
Change in practice-env. (Δ_{nt}) $\times$ Post-move $\times$ Females	-0.194*** (0.058)	-0.177** (0.074)	-0.258 (0.195)	-0.213 (0.178)
Panel C: Age < 35				
Change in practice-env. (Δ_{nt}) $\times$ Post-move $\times$ Age < 35	-0.157** (0.079)	-0.158* (0.091)	-0.162 (0.201)	-0.086 (0.166)
Panel D: Age $\geq$ 35				
Change in practice-env. (Δ_{nt}) $\times$ Post-move $\times$ Age $\geq$ 35	-0.090 (0.054)	-0.105* (0.063)	-0.162 (0.202)	0.041 (0.185)
Panel E: Higher pred. duration				
Change in practice-env. (Δ_{nt}) $\times$ Post-move $\times$ High risk job seekers	-0.123** (0.049)	-0.140** (0.063)	-0.325 (0.214)	0.043 (0.182)
Panel F: Lower pred. duration				
Change in practice-env. (Δ_{nt}) $\times$ Post-move $\times$ Low risk job seekers	-0.158** (0.079)	-0.164* (0.093)	-0.044 (0.191)	-0.124 (0.163)
Observations	114,385	114,385	76,129	76,105
Covariates	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Caseworker FE	✓	✓	✓	✓
Local Labor Market $\times$ Year FE	✓	✓	✓	✓

Notes: This table reports difference-in-differences estimates of the effects of broader referral environments on job seeker outcomes based on the sample data from 2004–2018, estimated separately by gender, age group, and predicted unemployment duration. The treatment variable measures changes in the referral environment faced by migrant caseworkers following inter-office moves. All specifications include covariates, year, caseworker, and local labor market-by-year fixed effects. Robust standard errors clustered at the caseworker level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

For male job seekers (Panel A), greater caseworker exposure to a broader referral environment is associated with small reductions in the probabilities of exiting unemployment within 90 and 180 days, although the estimates are mostly statistically insignificant. The corresponding estimates for female job seekers (Panel B) are larger and statistically significant. A 10 percentage point increase in the caseworker's exposure to a broader referral environment reduces the probability of exiting unemployment within 90 days by approximately 2.0 percentage points and the probability of exiting within 180 days by about 1.8 percentage points. These results suggest that caseworkers' exposure to a broader-referral environment may be more disruptive for women. One possible explanation is that women face different patterns of occupational sorting, job preferences, or

employment constraints, making referrals outside their preferred occupational domain more likely to generate job–person mismatch. However, because the estimates are obtained from interacted specifications, the difference between the male and female coefficients should be interpreted as evidence of heterogeneity only when the relevant interaction term or cross-group difference is itself statistically significant. The post-unemployment earnings estimates are small and statistically insignificant for both groups, providing little evidence that broader referral exposure affects earnings conditional on reemployment.

The age-specific estimates show a similar pattern. For job seekers younger than 35 (Panel C), a 10 percentage point increase in the caseworker’s exposure to a broader referral environment reduces the probabilities of exiting unemployment within both 90 and 180 days by approximately 1.6 percentage points, with the estimates statistically significant at conventional levels. For job seekers aged 35 and older (Panel D), the estimates are smaller and less precise. This pattern is consistent with younger job seekers being more sensitive to broader and potentially less tailored referrals. Younger workers may have less established occupational trajectories, shorter employment histories, or more fluid job preferences, which may make referrals outside their preferred occupations particularly disruptive. Older job seekers, by contrast, may possess more clearly defined skills and work histories, allowing them or their caseworkers to screen out poorly matched vacancies more effectively. Post-unemployment earnings effects also remain statistically insignificant across both age groups.

Finally, Panels E–F examine heterogeneity by predicted unemployment duration, which is used as a measure of baseline employability or expected difficulty in returning to work. The estimates indicate that job seekers with both lower and higher predicted unemployment duration are adversely affected by greater caseworker exposure to broader referral environments. Although the point estimates may differ somewhat across the two groups, the overall pattern is broadly similar, and there is limited evidence that the effect is concentrated exclusively among either relatively high- or low-risk job seekers. This suggests that the negative effects of broader referral environments are not confined to individuals with particularly weak labor-market prospects or, conversely, to those expected to return to work quickly.

Overall, the heterogeneity results suggest that the negative effects of broader referral environments are more pronounced among women and younger job seekers, while job seekers with lower and higher predicted unemployment duration appear to be affected in broadly comparable ways. A plausible mechanism is that exposure to the referral practices of peers or to a local practice environment encourages caseworkers to adopt broader and more standardized referral strategies. Such behavioral conformity may reduce the role of caseworker discretion and weaken the degree to which referrals are tailored to the characteristics of individual job seekers. The resulting increase in job–person mismatch may delay reemployment, particularly for groups whose occupational preferences, constraints, or labor-market attachment make them more sensitive to

poorly targeted referrals. At the same time, the absence of clear post-unemployment earnings effects suggests that broader referral environments primarily affect the timing of reemployment rather than the quality of the jobs obtained by those who eventually return to work. The findings therefore underscore the importance of preserving individualized caseworker assessment when referral practices spread across colleagues or offices. Although broader search environment may expand the set of vacancies considered, practice-environment-driven standardization may introduce short-term inefficiencies when it reduces the alignment between referrals and job seekers' skills, experience, and preferences.

8 Conclusion

This paper provides the first empirical evidence on how organizational environments shape caseworkers' vacancy referral behavior and, in turn, influence job seeker outcomes within public employment services. Using quasi-experimental variation from caseworker relocations across Swedish PES offices, I show that caseworkers systematically adjust their broader referral behavior to match the prevailing practice-environment of their new offices. Difference-in-differences and event-study estimates reveal sharp behavioral shifts at relocation with no anticipatory trends, and these adjustments persist over time. Peer-related influences appear to be an important component of the observed behavioral response, even after accounting for time-invariant office characteristics and local labor market conditions. The spillover operates symmetrically across transition types and does not vary systematically with tenure, suggesting that adaptation to the local referral environment may represent a relatively general feature of organizational adjustment. The magnitude of the spillover coefficient further indicates the degree of consistency in caseworkers' broader-referral behavior with prevailing practices at the destination office, highlighting the potential importance of the local work environment in shaping caseworker behavior.

These behavioral shifts have meaningful consequences for job seekers. Greater exposure to more broad referral environments significantly lowers short-term reemployment probabilities. Although post-unemployment earnings remain unaffected, the results indicate that these frictions weaken early job matching rather than long-term job quality. Placebo tests using predicted outcomes confirm that the findings are not driven by selection or other caseworker functions, strengthening the causal interpretation. Heterogeneity analyses further indicate that these adverse effects are concentrated among women, and younger job seekers. For women, the effect may reflect greater mismatch in applications to broader occupations, arising from gender differences in occupational sorting, job preferences, or weaker application quality. For younger workers, broader referral environment may be particularly disruptive because they tend to have less established occupational trajectories, shorter employment histories, and more fluid job

preferences, making referrals outside their preferred occupations potentially more consequential.

Overall, the findings suggest that caseworkers' exposure to offices with higher broader-referral intensity may contribute to short-term mismatches for their job seekers. Although broader-referral environments may encourage caseworkers to expand the range of vacancies to which job seekers are referred, this may also weaken the alignment between job seekers and suitable vacancies. These findings add nuance to the comparison with Van der Klaauw and Vethaak (2022); however, the general lesson is that broader referral environment may not necessarily be beneficial when it weakens the fit between job seekers and vacancies. At the same time, the results also contrast with Belot et al. (2019; 2022), who show that flexible, information-based interventions can benefit highly disadvantaged workers. It is important to re-emphasize, however, that the comparison here is between more versus less broad referral environments, rather than evaluating broader referrals in isolation. The absence of long-term earnings penalties, on the other hand, may suggest that the associated inefficiencies are transitory. More broadly, the results underscore the important role of peers and local institutional cultures in shaping frontline implementation of labor market policy. Designing referral systems that foster organizational learning while preserving client-centered discretion may help reduce mismatches and enhance the effectiveness of public employment services.

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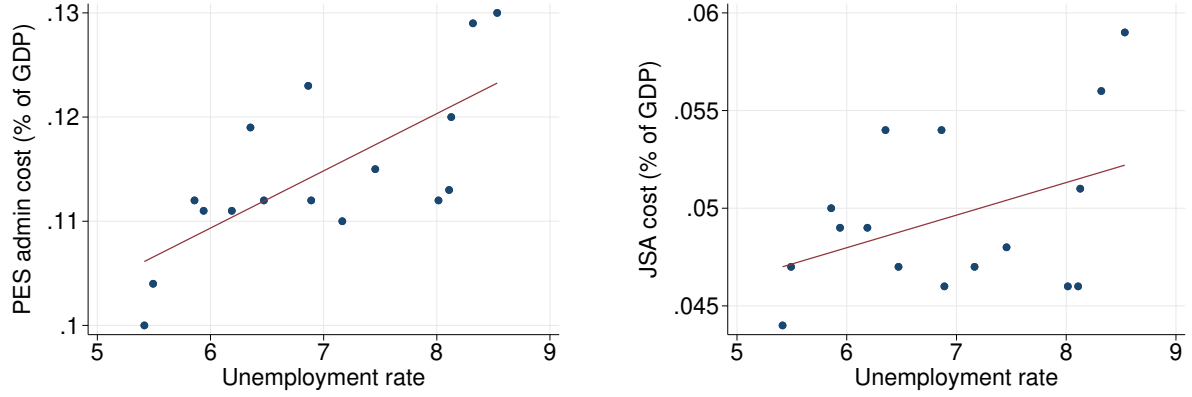
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Appendix

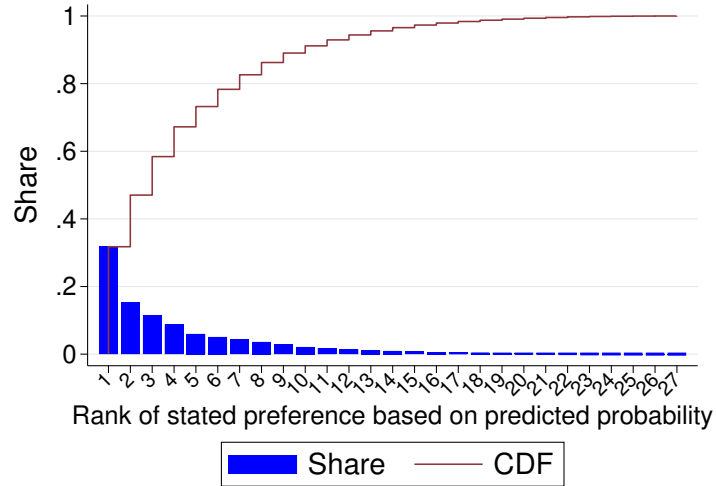
Descriptive statistics

Figure A1: Relationship between unemployment rate, public employment service spending, and JSA spending in European countries



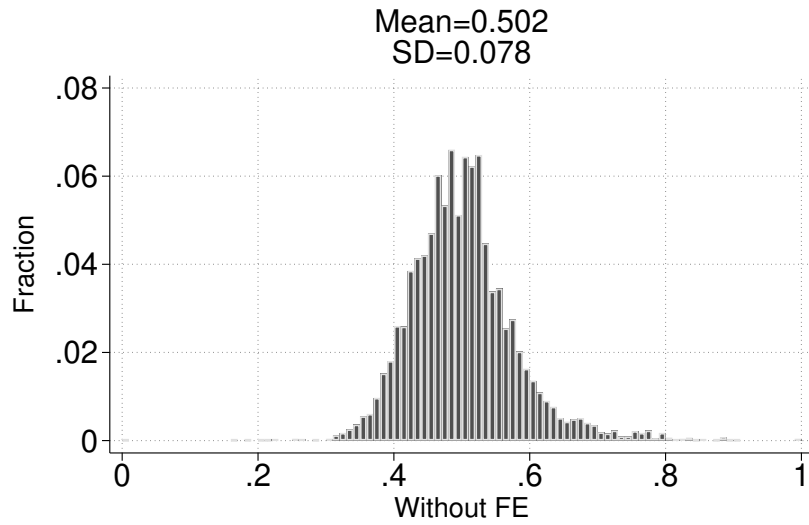
Notes: The figures present binscatter plots of OECD region-year observations showing the relationship between unemployment rates and (i) public employment service (PES) administrative expenditures and (ii) job-search assistance (JSA) expenditures, both expressed as a percentage of GDP using OECD country-year observations from 2005–2020. Each point represents the average value within equally sized bins of the unemployment rate distribution. The solid line indicates the fitted linear regression. The figures are descriptive and illustrate the positive association between unemployment and PES and JSA spending.

Figure A2: Are stated preference of job seekers relevant?



Notes: This figure shows the relationship between job seekers' stated and predicted preferences based on the sample data from 2004-2018. The x-axis ranks stated preferences by predicted probability of choosing that occupation by a job seeker conditional on job seekers characteristics, and the y-axis shows the share of job seekers. Blue bars depict the distribution of stated preferences, while the maroon line represents the empirical cumulative distribution function (CDF).

Figure A3: Practice Environment of Migrant Caseworkers



Notes: Based on the sample data from 2004–2018, figure A3 shows the distribution of practice environments across the offices to which migrant caseworkers are assigned. This represents a raw, cross-sectional distribution that captures differences in referral practices across offices. The wide dispersion highlights substantial within-caseworker variation, which is essential for empirical identification.

Table A1: Are movers different than stayers?

	(1) Mover's dummy
# of referrals per caseworker in a year	-0.000 (0.000)
# of job seekers per caseworker per year	0.000 (0.000)
Average # of meetings per job seeker	0.000 (0.000)
Origin Office FE	✓
Destination Office FE	✓
Year FE	✓
Observations	36,876
R-squared	0.405

Notes: This table presents diagnostic regressions examining whether movers differ systematically in their observable characteristics from stayers using caseworker-year-level data from 2004–2018. The dependent variable is the mover dummy. Each coefficient represents the partial association between the characteristic and the likelihood of moving. All regressions include origin and destination office fixed effects as well as year fixed effects. Standard errors are clustered at the caseworker level and shown in parentheses. Asterisks ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table A2: Do changes in practice-environment affect migrant caseworkers' other traits?

	(1) Δ_{nt}
# of referrals per caseworker in a year	0.000 (0.000)
# of job seekers per caseworker per year	-0.000 (0.000)
Average # of meetings per job seeker	0.000 (0.000)
Caseworker FE	✓
Year FE	✓
Observations	6,605
R-squared	0.454

Notes: This table reports diagnostic regressions testing whether changes in the practice environment of movers affect other observable caseworker characteristics using caseworker-year-level data from 2004-2018. The dependent variable is the change in practice environment (Δ_{nt}). All specifications include caseworker and year fixed effects. Standard errors are clustered at the caseworker level and shown in parentheses. Asterisks ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.