Search Effort, Worker Attachment, and Labor Market Power

Dominik Wehr *

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Abstract

Firms' wage-setting power is limited by workers' outside options, which depend not only on the offers workers receive but on the offers they generate through costly search. This paper studies how search decisions and heterogeneous preferences over jobs jointly shape labor supply to firms. Using survey information on search behavior linked to Swedish employer–employee records, I show that search effort declines along the job ladder but remains substantial at top-ranked firms, where idiosyncratic, non-pecuniary reasons dominate.. Search is persistent and concentrated among a small group of workers. Guided by these facts, I develop a dynamic model with endogenous search effort and heterogeneous preferences. Higher pay retains workers both by making competing offers less attractive and by reducing search effort, which lowers their exposure to those offers. Relative to a benchmark that eliminates search responses, endogenous search raises the firm's labor supply elasticity from 3.66 to 4.98, an increase of 36 percent, and lowers the implied markdown from 27 to 20 percent of pay. I show that aggregating individual search responses into firm labor supply requires accounting for both preference heterogeneity and the offer-arrival process.

*Dominik Wehr: Stockholm School of Economics, dominik.wehr@phdstudent.hhs.se. I am grateful to my advisors Lars Ljungqvist and Arash Nekoei, and to Benjamin Schoefer and Jósef Sigurdsson for their support. I thank Miren Azkarate-Askasua, Edoardo Acabbi, Sydnee Caldwell, David Card, Mitchell Downey, Tore Ellingsen, Lukas Freund, Axel Gottfries, Pat Kline, Martin Koenen, Moritz Kuhn, Kieran Larkin, Andreas Mueller, Ayşegül Şahin, David Seim, Giulia Vattuone, Stefano DellaVigna, as well as seminar and conference participants at the Society of Labor Economics World Congress, Sophia University, the Institute for Research on Labor and Employment, the First Aarhus Workshop on Labor Markets, Stockholm University, Econometric Society World Congress, the IWH Senior Workshop on Future Labour Markets, the Annual Search and Matching Conference, and the Annual Conference of the European Association of Labour Economists, for constructive comments.

1 Introduction

A firm's wage-setting power is constrained by its workers' outside options. These options reflect both the jobs workers can access and how they value those alternatives relative to their current employment. In the benchmark monopsony framework, the individual firm takes the distribution of workers' outside options as given (Kline, 2025). Evidence on offer acceptance within a given choice set reveals workers' willingness to move, but does not by itself establish how they acquire those alternatives. Workers partly generate their own outside options through costly search. Limited exposure to competing employers can therefore reflect not only barriers to finding another job, but also workers' attachment to their current one: those who value their current match more have less to gain from seeking alternatives. Higher pay can consequently retain workers both by making competing offers less attractive and by discouraging search. Yet little is known empirically about how this interaction between search decisions and preferences shapes firms' wage-setting power. Quantifying it requires jointly measuring how search responds to pay, how effectively it generates offers, and how heterogeneous search responses translate into firm-level employment.

In this paper, I combine new evidence on realized on-the-job search with a dynamic model to quantify how search decisions and worker attachment jointly shape labor supply to firms. I document how search effort and the reasons driving it vary across employers and evolve within continuing employment relationships. These patterns guide the specification and estimation of a model of costly search with persistent but evolving match-specific amenities. The central finding is that strong incumbent attachment coexists with a sizable contribution of endogenous search effort to firms' labor supply. At the same time, heterogeneity in attachment attenuates this contribution relative to what the average search response would imply. The contribution of search effort depends not only on how strongly search effort responds to pay, but also on whose search behavior changes and how those changes translate into lasting employment.

Existing data sources rarely combine direct observations of search behavior, employer identities, and repeated observations of the same worker. Exploiting a large labor force survey, linked to Swedish matched employer–employee records and firm balance sheets, this paper brings these elements together. Firm-level data on pay premia and productivity facilitate transparent rankings of firms and allow me to locate workers on a well-defined job ladder. Self-reported information on search behavior then sheds light on how search effort, and the reasons that motivate workers to search, vary across firms. Observing the same workers over eight quarters reveals both persistent differences in search behavior and systematic changes within ongoing employment relationships. Finally, information on how new hires came into contact with their employer, whether the worker or the firm initiated it, links search to the offers it generates and reveals how much mobility occurs without active search.

The empirical analysis establishes three main findings. First, on-the-job search declines along the job ladder. When firms are ranked by value added per worker, the share of workers actively searching falls from 10.8 percent at the 5th percentile to 5.4 percent at the 95th. The gradient is much flatter when firms are ranked by their pay premia instead. Evidence on job satisfaction and

workplace amenities suggests that this contrast partly reflects compensating differentials: pay premia do not fully capture the employer characteristics that matter for search. Workers' efforts to generate outside options thus vary systematically with the quality of their current employer, yet search remains substantial even at top-ranked firms.

Second, I show that idiosyncratic, non-pecuniary reasons account for a large share of search throughout the firm distribution. Self-reported information on reasons for search allows me to decompose both the decline in search along the job ladder and the substantial search that remains at top-ranked firms. Higher pay, the anticipation of job loss, and the desire to increase working hours are important motives at lower-ranked firms and become less frequent moving up the ladder. In contrast, the combined incidence of search due to idiosyncratic, non-pecuniary motives remains stable throughout the firm distribution. These motives account for most search at the highest-ranked firms, while the desire to try something new alone is stated as the main reason for search by more than 40 percent of searchers at the top. Self-reported reasons align with workers' employment conditions and subsequent transitions. Job demands and unfavorable schedules predict the corresponding reasons for search, while workers searching in anticipation of job loss are substantially more likely to leave employment. While search incentives related to pay, hours, and employment security diminish along the firm ladder, heterogeneous non-pecuniary preferences sustain expected gains from mobility throughout the employer distribution.

Third, I document persistent differences in search behavior among workers, even conditional on employer quality. Repeated observations of the search actions taken by a worker within the same job distinguish occasional search actions spread across many workers from persistent episodes of search activity by a few workers. The data clearly point to the latter. Search is highly concentrated throughout the firm distribution: across employer ranks, the share of workers observed searching at least once across eight quarterly interviews never exceeds 25 percent, substantially less than expected if every worker in the same firm searched with the same probability. Active search is therefore concentrated in a small subset of workers, who search repeatedly over time, while incumbents with high tenure exert little search effort. Yet this heterogeneous attachment is not necessarily permanent, as search effort tends to increase with tenure within existing employment spells, predominantly because workers want to try something new. I show that job satisfaction declines prior to employer transitions, consistent with movers selecting on negative shocks. Together, these findings suggest that evolving match-specific amenities generate heterogeneity in outside options within the firm.

To establish the implications of these findings for firm labor supply, I develop a stylized wage-posting model with endogenous search and heterogeneous worker attachment. Relative to a benchmark that fixes workers' baseline search policies while allowing offer acceptance to adjust, endogenous search amplifies retention by slowing down the arrival of competing offers. With homogeneous workers, this margin can be quantified conditional on knowing how search responds to pay and the offer arrival process. With heterogeneous attachment, however, the average search response is no longer sufficient. A reduction in search prevents more quits when it occurs

among workers more likely to accept outside offers, and each prevented quit contributes more to long-run labor supply when it preserves a durable match. To shed light on the interaction of preference heterogeneity with the offer arrival process, I decompose the additional amplification from search into three components: the average search response, selection through offer acceptance, and differences in remaining match duration across workers. Even a causal estimate of the average search response therefore does not generally identify the contribution of search to firm labor supply.[1]

The stylized model highlights the necessary ingredients for translating heterogeneous search responses into firm labor supply. Quantifying the contribution of search effort requires recovering objects that are not directly observed in the data: the offer arrival process, workers' search responses to pay, and the acceptance probabilities and expected remaining match durations of those whose search behavior changes. I therefore bring this framework to the data by estimating a richer dynamic model of random search with three additional features that emerge from the empirical analysis. First, to capture the fact that few workers engage in active on-the-job search, the model treats costly search as a binary choice. Active search increases the arrival rate of offers at a substantial fixed cost. Second, in line with workers' self-reported reasons for search, I allow jobs to differ in pay, hours mismatch, and contract type. Contract expiration and advance layoff notice allow workers to search in anticipation of job loss. Third, motivated by the prevalence of idiosyncratic motives and the rise in search over the course of continuing employment spells, workers have idiosyncratic valuations of jobs that are persistent but can change within an ongoing employment relationship. While match-specific amenities provide a source of sorting, adverse changes induce renewed search even in highly durable matches. The model therefore accommodates search for better matches rather than only for higher-ranked employers, providing a source of search throughout the firm distribution that mirrors the roughly constant incidence of search motivated by the desire to try something new.

To recover the processes underlying offer arrival, search costs, and workers' preferences, I develop an identification strategy that builds on joint evidence on search behavior, hiring channels, and subsequent employer mobility. The first empirical challenge consists of separating offer generation from offer acceptance. I show that differences in employer mobility between searchers and nonsearchers, combined with the share of worker-initiated hires, discipline how strongly offers depend on search, as well as the link between workers' willingness to move and their search behavior. The second challenge is the identification of unobserved heterogeneity in worker attachment. The persistence of search within an employment spell, documented through repeated observations of search actions, distinguishes persistent preference heterogeneity from transitory search costs. Together with the search gradient across employers, this persistence pins down preference heterogeneity and the scale of search costs, allowing the model to distinguish the

[1]This aggregation problem parallels heterogeneous-agent models in which aggregate effects depend on the joint distribution of individual responsiveness and economic exposure (Auclert, 2019; Patterson, 2023). In this setting, offer acceptance and remaining match duration determine how heterogeneous search responses translate into firm employment.

behavioral response to employer pay from endogenous match selection. Search rates among workers in long-tenure matches further inform the frequency of amenity changes.

The model reproduces a range of untargeted moments relevant for the labor-supply analysis. Since employment transitions depend jointly on the arrival of offers and workers' willingness to accept them, I assess these components separately. Unsolicited-offer arrival rates are broadly consistent with Faberman et al. (2022). In addition, the gap in acceptance rates between active searchers and nonsearchers is 38.5 percentage points in the model, compared with 38.2 in their data, supporting the model's account of selection into search. I also assess whether the model generates the persistent differences in worker attachment that shape search incentives. The model reproduces the concentration of active search over time, with approximately 80 percent of workers never observed searching across eight quarterly interviews. Its implied strength of incumbent attachment is also broadly consistent with stated-preference evidence: approximately 35 percent of workers prefer their current job to an alternative offering 20 percent higher pay, compared with 39 percent in Caldwell et al. (2025). Overall, these comparisons lend credibility to the model's quantitative account of how search behavior and preference heterogeneity shape labor mobility.

Despite substantial incumbent attachment, endogenous search makes a sizable contribution to firm labor supply. I quantify this contribution by comparing the response to a permanent change in employer pay with a benchmark that holds baseline search behavior fixed. Outside opportunities remain fixed, while offer acceptance and workforce composition adjust in both cases. Allowing search to respond raises the firm's stationary labor supply elasticity from 3.66 to 4.98, an increase of 36 percent. Search adjustment thus accounts for about 27 percent of the firm's labor supply elasticity. The additional response operates through retention: higher pay not only makes competing offers less attractive but also reduces incumbents' exposure to them — a 1 percent pay increase reduces outside-offer arrivals by about 2.2 percent. Random search with atomistic employers implies that the recruitment elasticity is unchanged, introducing an asymmetry between recruitment and retention, which are symmetric in benchmark models (Manning, 2021; Card, 2022). Under the standard monopsony pricing condition, the implied markdown, measured as the gap between pay and marginal revenue product relative to pay, falls from 27 percent to 20 percent. Inferring wage-setting power from acceptance responses alone would thus overstate it by about a third.

The amplification from endogenous search depends crucially on heterogeneity in preferences and the offer arrival process. Persistent preferences support sorting into valued matches and imply that a large share of workers in the model are highly attached to their job. These inframarginal workers reject most offers irrespective of small changes in firm pay, and in line with the data rarely incur the high fixed costs of active search. Meanwhile, workers whose match has recently deteriorated, or whose contract is about to expire, make up a disproportionate share of the pool of searchers. These workers are highly willing to accept outside offers and their decision to actively search is inelastic to pay. Changes in the firm pay policy therefore mainly affect the search decisions of marginal workers, whose moderate attachment places them close to the search threshold.[2] For a

[2]The role of workers near the search threshold parallels the aggregation of discrete adjustment decisions in Caballero

small change in pay, 20 percent of incumbents account for 83 percent of the decline in active search. The implications of this heterogeneity are twofold. First, relative to the average active searcher, marginal workers are more attached and less willing to accept outside offers: the least attached workers continue searching despite a small raise. Reducing marginal workers' search therefore prevents fewer quits than the average-search benchmark implies. Acceptance weighting lowers the average search elasticity from 10.1 to 8.6. Second, at the margin a pay raise preserves fragile matches: workers retained through lower search effort have an expected remaining tenure about 35 percent shorter than the duration implied by the average separation rate. Together, these forces render the contribution of search 44 percent smaller than implied by the average search response, the object a randomized change in pay would identify. Strong incumbent attachment can therefore coexist with highly responsive search at the margin and a substantial contribution of search adjustment to firm labor supply. The size of this contribution cannot be inferred from average search responsiveness alone: preferences shape which workers reduce their search, whether they would otherwise accept outside offers, and how long the matches preserved through lower search would last.

The paper contributes to three strands in the literature. First, it contributes to a central frontier of the monopsony literature emphasized by Kline (2025): the microeconomic foundations of firm labor supply and wage-setting. Search frictions and preference heterogeneity are well-established sources of monopsony power, but direct evidence on how they interact through workers' search decisions remains scarce. Berger et al. (2024) combine worker–firm-specific preferences and search frictions in a bargaining model with endogenous vacancy creation but exogenous worker search participation. I instead study endogenous worker search under wage posting: attachment to the current employer governs both the incentive to seek outside offers and the willingness to accept them.[3] By distinguishing changes in offer generation from changes in acceptance, the analysis complements evidence on quits (Bassier et al., 2022), recruitment (Dal Bó et al., 2013; Falch, 2017; Belot et al., 2022; Datta, 2023), and interview acceptance and wage-setting conduct (Roussille and Scuderi, 2026).

Most closely related, Caldwell et al. (2025) elicit workers' pay beliefs and preferences over named employers. They document substantial incumbent attachment and show that more attached workers report a lower willingness to search. I build on this mechanism by using realized search, subsequent mobility, and information on the offer arrival process to quantify how preferences and endogenous search together shape the labor supply elasticity facing the firm. In particular, aggregating heterogeneous search responses into this elasticity requires accounting for how many quits these responses prevent and how long the retained matches last. Unsolicited offers, which their analysis abstracts from, are crucial to this aggregation.

Second, this paper contributes to the literature on job amenities, compensating differentials,

and Engel (1991, 1993), where aggregate responsiveness depends on the distribution of agents relative to their adjustment thresholds.

[3] In the random-search model with atomistic employers studied in this paper, allowing search to adjust increases the retention elasticity while leaving the local recruitment elasticity unchanged relative to holding search at its baseline policy. This qualifies the recruitment–retention symmetry of some benchmark models (Manning, 2021; Card, 2022).

and worker sorting. Experiments and surveys document substantial heterogeneity in workers' valuations of non-wage attributes (Mas and Pallais, 2017; Wiswall and Zafar, 2018; Maestas et al., 2023), while complementary approaches recover job values from wages, worker flows, and firm data to study mobility and inequality (Sorkin, 2018; Hall and Mueller, 2018; Taber and Vejlin, 2020; Sockin, 2022; Lamadon et al., 2022; Morchio and Moser, 2026). Recent work measures valuations of particular jobs and employers more directly: Humlum et al. (2025) document pay–amenity trade-offs among movers, including between the same pair of firms, while Caldwell et al. (2026) elicit amenity valuations through choices over offers at named employers. Other work emphasizes unemployment risk (Jarosch, 2023) and hours mismatch (Carry, 2024; Lachowska et al., 2026) as dimensions of job quality. Fujita (2010) documents the importance of non-wage motives for on-the-job search. I bring these considerations together in a reduced-form decomposition of search by motive across the market-wide distributions of firm pay premia and productivity. This decomposition quantifies the relative contributions of pay, hours, precautionary search, education–job mismatch, working conditions, and idiosyncratic non-wage motives. Longitudinal observations extend the decomposition to within-match dynamics.

Third, this paper contributes to research on endogenous on-the-job search. Models of optimal search effort connect workers' incentives to search to wage dispersion and sorting (Postel-Vinay and Robin, 2004; Christensen et al., 2005; Bagger and Lentz, 2019), precautionary savings (Lise, 2013; Simmons, 2024), and aggregate labor market fluctuations (Nagypál, 2007; Eeckhout and Lindenlaub, 2019; Afrouzi et al., 2026; Pilossoph et al., 2026). A small set of papers estimate models using revealed search behavior and subsequent outcomes. In a seminal contribution to this literature, Faberman et al. (2022) use direct evidence on search effort, offer arrivals, and acceptance to study business cycle amplification arising from endogenous search. Kaas et al. (2026) estimate a model of wealth and discrete search choices using data on search and observed transitions. Recent work in Faberman et al. (2026) incorporates non-wage amenities into endogenous-search models to study gender wage differences. My contribution is twofold. First, I develop and estimate a wage-posting framework with match-specific amenities in which firm pay premia, directly estimated from matched employer–employee data, discipline the wage returns to search. Second, I incorporate rich match-specific preference dynamics, disciplined by longitudinal search choices, to quantify selection into active search. Together, these features provide a new empirical foundation for assessing firm wage-setting: counterfactual changes in firm pay premia account for both workers' wage incentives and the preference heterogeneity shaping who searches and accepts offers. This allows me to isolate the contribution of endogenous search to firm-level labor supply elasticities.

The remainder of the paper is organized as follows. Section 2 presents a stylized model that decomposes the contribution of endogenous search effort to firm labor supply and shows how it depends on preference heterogeneity and the offer arrival process. Section 3 describes the institutional setting and the linked survey and administrative data, and introduces rankings of firms. Section 4 documents how search varies across firms, the motives that sustain search at top-ranked firms, and how search and job satisfaction evolve within employment spells. Section 5

develops the quantitative model and discusses identification and estimation. Section 6 assesses fit and external validity and quantifies the implications for firm labor supply. Section 7 concludes.

2 Stylized Model

To understand how search effort shapes the firm's labor supply, I introduce a stylized model combining costly on-the-job search (Christensen et al., 2005; Faberman et al., 2022) with random-utility offer acceptance (Card et al., 2018). Higher pay retains workers both by making competing offers less attractive and by reducing their incentive to devote effort to generating offers. The magnitude of this endogenous offer channel depends on whose search effort responds to pay, whether the forgone offers would have been accepted, and how long the workers retained would remain. The relationship between offers and search determines how individual search responses must be aggregated to recover their contribution to the firm's labor supply.

Environment. Time is continuous. Atomistic employers post wages, and search is random. A permanent pay change at a single employer leaves the value of employment at other firms, the value of unemployment, and search at other employers unchanged. Search effort changes the arrival rate of offers but not their distribution. Preferences are linear. A worker employed at wage $w > 0$ receives flow payoff $w + q$. The match amenity q is drawn when a job is offered, observed before acceptance, and fixed within the match. Workers discount the future at rate $\rho > 0$ and separate into unemployment at rate $\delta \geqslant 0$. Search effort $s \geqslant 0$ costs $c(s)$, where c is increasing and twice differentiable, satisfying $c''(s) > 0$, and $c(0) = 0$. Offers arrive at rate $\lambda(s) = \lambda_0 + \lambda_1 s$, with $\lambda_0 \geqslant 0$ and $\lambda_1 > 0$. Unsolicited and search-generated offers are drawn from the same distribution. The *active share of offers* is defined as the fraction of a worker's offers that her own search generates:

$$\theta(s) = \frac{\lambda_1 s}{\lambda_0 + \lambda_1 s}. \tag{1}$$

Because the two channels are additive and unsolicited offers arrive at a constant rate, the share depends only on how much the worker searches.

Search responds to the gains from moving. Let $V(w, q)$ be the current job's value and F the distribution of outside employment values. Conditional on receiving an offer worth v, workers draw independent, mean-zero type-I extreme-value shocks to moving and staying, with scale $\sigma > 0$. These shocks are independent across offers and distinct from the persistent amenity q. With $\Lambda(z) = (1 + e^{-z})^{-1}$, the expected gain from an offer and its acceptance probability are

$$\Omega(V) = \sigma \int \log\left(1 + e^{(v-V)/\sigma}\right) \, dF(v), \qquad A(V) = \int \Lambda\left(\frac{v - V}{\sigma}\right) \, dF(v). \tag{2}$$

Since $\Omega'(V) = -A(V)$, a more valuable current job reduces the expected gain from outside offers. The value of employment satisfies the Bellman equation

$$\rho V(w, q) = w + q + \delta[U - V(w, q)] + \max_{s \geqslant 0}\{-c(s) + \lambda(s)\Omega(V(w, q))\}. \tag{3}$$

At an interior optimum, $c'(s) = \lambda_1 \Omega(V)$, implying

$$\frac{\partial s}{\partial V} = -\frac{\lambda_1 A(V)}{c''(s)} < 0. \tag{4}$$

Higher pay therefore reduces both the probability that outside offers are accepted by incumbent workers, and the effort devoted to generating offers.

Individual Behavioral Responses. I now describe the problem faced by the firm. The central object of interest is the elasticity of the firm's stationary employment with respect to its pay, ε^N. Under wage posting, this elasticity measures the firm's wage-setting power: a profit-maximizing employer sets pay below the marginal revenue product of labor by the markdown $1/\varepsilon^N$. Therefore, the more elastic the labor supply it faces, the less of the surplus it retains. Labor supply to the firm is determined by two objects, recruitment and quits. Let $Q(w, q) = \lambda(s(w, q))A(V(w, q))$ denote the quit hazard of a worker earning w with match-specific amenity q. Analogously, let $r(w, q)$ denote recruitment. Then, stationary employment in amenity state q is given by $n(w, q) = r(w, q)/[\delta + Q(w, q)]$. Total employment at wage w is obtained by aggregating over all possible match values, $N(w) = \int n(w, q)\, dq$.

To understand the firm's wage-setting power, consider a small change in the firm's wage away from baseline wage w_0. Let $g(q) = n(w_0, q)/N(w_0)$ be the incumbent distribution. Let ε^X denote the elasticity of X with respect to employer pay at this baseline. Differentiating stationary employment gives

$$\varepsilon^N = \mathbb{E}_g[\varepsilon^r] - \mathbb{E}_g\left[\frac{Q}{\delta + Q}\varepsilon^Q\right], \qquad \varepsilon^Q(q) = \varepsilon^A(q) + \theta(q)\varepsilon^s(q). \tag{5}$$

The quit response combines changes in acceptance conditional on an offer with changes in exposure to offers. The latter is scaled by the worker's active share, $\theta(q)$. These state-specific responses enter the employment elasticity with weights reflecting both incumbent employment shares and the share of separations accounted for by quits. Average acceptance and search responses therefore do not generally suffice to recover the employment response. The recruitment margin contains no analogous contribution of search: with atomistic employers and random search, outside workers' search does not respond to a single firm's pay. Higher pay attracts new hires through higher acceptances, while retaining incumbents through both lower acceptance of competing offers and reduced arrival of offers. The direct search-adjustment margin therefore operates solely through retention.

2.1 Aggregating Individual Responses

To quantify the contribution of endogenous search to the firm's labor supply elasticity, I now aggregate these individual responses. I isolate the search contribution by comparing endogenous search (E) with a counterfactual (C) that holds the baseline policy $s(w_0, q)$ fixed when pay changes. Acceptance and workforce composition adjust in both cases. At the common baseline, recruitment and acceptance have identical local responses, so the difference in employment elasticities isolates the contribution of search.[4]

Let $\Delta\varepsilon^N = \varepsilon^{N,E} - \varepsilon^{N,C}$ denote the contribution of search to the firm's employment elasticity, $D(q) = -\varepsilon^s(q) \geqslant 0$ the magnitude of the individual search response, and $T(q) = 1/[\delta + Q(q)]$ expected remaining tenure. All objects are evaluated at the common baseline.[5]

For a worker in state q, the search response reduces offer arrivals by $\lambda_1 s(q)D(q)$ per unit increase in log pay. A fraction $A(q)$ of these forgone offers would have induced a quit, and each prevented quit preserves $T(q)$ expected units of employment. Aggregating these individual contributions using baseline employment shares gives

$$\Delta\varepsilon^N = \lambda_1 \mathbb{E}_g[s(q)A(q)D(q)T(q)]\,. \tag{6}$$

The aggregate contribution therefore depends on the joint distribution of individual search responses and their employment weights, $\lambda_1 s(q)A(q)T(q)$.

Homogeneous attachment. Transitory choice shocks, as assumed in Sorkin (2018), imply that preferences do not enter as a separate state. With homogeneous attachment, incumbents share the same search policy, acceptance probability, and expected remaining tenure. The search response is also common, $D(q) = D$, so the search contribution satisfies

$$\Delta\varepsilon^N = \underbrace{\frac{Q}{\delta + Q}}_{\text{Quit Share}} \underbrace{\theta}_{\text{Active Offer Share}} \underbrace{D}_{\text{Search Response}}\,. \tag{7}$$

The contribution of endogenous search to the labor supply elasticity can thus be pinned down by three objects: i) quit share, ii) the elasticity of search with respect to pay, and iii) active offer share. This benchmark allows transitory choice shocks. I next examine persistent differences in attachment, which are permanent in the stylized model.

Heterogeneous attachment. With heterogeneous attachment, the same average search response can preserve different amounts of employment depending on who responds. Three averages organize the result. I suppress the dependence of all objects on q. Let $\bar{s} = \mathbb{E}_g[s]$ be the average

[4] Because the baseline search policy is optimal, the envelope theorem gives $V^E_w = V^C_w = 1/(\rho + \delta + Q)$ at w_0.

[5] Assume a differentiable stationary baseline with positive average search and finite employment, expected durations, and required moments. At differentiable zero-search states set $D = 0$; zero-offer contributions are defined by the final expression in equation (6).

search rate and $\mathbb{E}_s[Z] = \mathbb{E}_g[sZ]/\bar{s}$ the search-weighted average. This is the average a pay experiment recovers: a small permanent pay change among baseline incumbents, measured before composition adjusts, identifies $\mathbb{E}_s[D]$, the search-weighted average of individual responses.[6] For employment, responses must also be weighted by whether the forgone offers would have been accepted; let $\mathbb{E}_{sA}[Z] = \mathbb{E}_g[sAZ]/\mathbb{E}_g[sA]$ be the average weighted by the quits that search generates. The two averages differ whenever acceptance varies across searchers. Finally, let $\bar{Q} = \mathbb{E}_g[Q]$ and $\bar{S} = \delta + \bar{Q}$ be the average quit and separation hazards, and $\theta^Q = \lambda_1 \mathbb{E}_g[sA]/\bar{Q}$ the share of quits generated through active search. The following proposition characterizes the contribution of search at the firm level.

Proposition 1 (The contribution of search to firm labor supply)**.** *Under the stated assumptions, the additional stationary labor supply elasticity from endogenous search is*

$$\Delta\varepsilon^N = \theta^Q \frac{\bar{Q}}{\bar{S}} \left\{ \underbrace{\mathbb{E}_s[D]}_{\text{average search response}} + \underbrace{\frac{\mathrm{Cov}_s(A, D)}{\mathbb{E}_s[A]}}_{\text{acceptance selection}} + \underbrace{\mathbb{E}_{sA}[D(\bar{S}T - 1)]}_{\text{workforce adjustment}} \right\}. \tag{8}$$

The contribution is strictly positive whenever search falls on a positive mass of incumbent matches with positive acceptance probability. With homogeneous incumbents, both corrections vanish and the expression reduces to equation (7)*.*

The multiplier is the share of all separations generated through active search. The first term applies this share to the magnitude of the experimental search response. Acceptance selection reweights that response by the probability of accepting an offer. It is negative when larger proportional search responses occur among workers with lower acceptance probabilities. Workforce adjustment then accounts for the remaining tenure of the matches whose quits are prevented. It is negative when these prevented quits preserve less employment on average than the common-duration benchmark $1/\bar{S}$. Neither correction has a predetermined sign. Section 6.4 quantifies both corrections. Appendix C provides the derivation.

The Role of the Offer Arrival Process. To isolate how offer arrivals shape the aggregation weights, set $\delta = 0$. Then $A(q)T(q) = 1/\lambda(s(q))$: a higher acceptance probability produces more prevented quits, but each preserves less expected employment. The contribution simplifies to $\Delta\varepsilon^N = \mathbb{E}_g[\theta D]$, where $\theta(q) = \theta(s(w_0, q))$, while the aggregate search response weights individual elasticities by baseline search. Define the pooled active share of offers as $\bar{\theta} = \lambda_1 \bar{s}/(\lambda_0 + \lambda_1 \bar{s})$.[7] Rearranging gives

$$\Delta\varepsilon^N = \underbrace{\bar{\theta}\, \mathbb{E}_s[D]}_{\text{Average Response}} - \underbrace{\bar{\theta}\, \frac{\mathrm{Cov}_g(s, D)}{\bar{s}}}_{\text{Heterogeneity}} + \underbrace{\mathbb{E}_g\big[D(q)\big(\theta(q) - \bar{\theta}\big)\big]}_{\text{Interaction}}. \tag{9}$$

[6] See Appendix C.5 for more details.

[7] This pooled share weights workers by their total offer arrivals. The incumbent mean $\mathbb{E}_g[\theta]$ and the active share of quits θ^Q use different weights.

The first term scales the magnitude of the experimental search response by the pooled active share. The heterogeneity correction converts the search-weighted mean into the incumbent-weighted mean; it is negative when workers who search more have larger proportional responses. The interaction term then replaces the pooled active share with each worker's own active share. Together, the two corrections show why the average search response need not suffice for the employment effect.

If all offers are search-generated, $\theta(q) = \bar{\theta} = 1$. The interaction term vanishes, leaving $\Delta\varepsilon^N = \mathbb{E}_g[D]$. Workers who search little generate fewer offers, but preventing one of their offers preserves more employment. These effects offset, so the relevant average gives each incumbent equal weight. If unsolicited arrivals instead dominate throughout the workforce, $\lambda_1 s(q) \ll \lambda_0$, then $\theta(q) \approx \lambda_1 s(q)/\lambda_0$ and $\bar{\theta} \approx \lambda_1 \bar{s}/\lambda_0$. The interaction term approximately offsets the heterogeneity term, leaving $\Delta\varepsilon^N \approx \bar{\theta}\mathbb{E}_s[D]$. Each prevented offer now preserves approximately $1/\lambda_0$ units of employment, so the absolute reduction in search determines the employment effect. The experimental search response therefore approximately suffices, given the pooled active share of offers. With exogenous separations or evolving match states, the general duration weights remain relevant.

Implications for the empirical analysis. Strong incumbent attachment need not imply a small contribution of search to firm labor supply, and a large average search response need not imply a large one. To quantify the contribution, the empirical analysis documents the search–pay gradient, the importance of unsolicited offers, and the motives, persistence, and evolution of search within matches. The quantitative model combines this evidence with hiring channels and subsequent mobility to estimate the offer arrival process, the search elasticity, and the joint distribution of individual search responses, acceptance, and remaining tenure. It accounts for sorting in the observed search–pay gradient and allows attachment to evolve, so that duration weights reflect both current attachment and its persistence. I then use these estimated objects to quantify the contribution of endogenous search to firm labor supply and how heterogeneous attachment shapes its magnitude.

3 Institutional Setting and Data

3.1 Institutional Setting

Wage-Setting The Swedish labor market is largely regulated through collective bargaining agreements. Between 2005 and 2019, collective agreements covered around 90 percent of Swedish employees and 85 percent of private-sector employees (Medlingsinstitutet, 2021). Rather than setting wages directly, the agreements provide general frameworks for the wage-setting process.[8]

[8]According to Fredriksson and Topel (2010), 36 percent of employees are subject to agreements stipulating bilateral bargaining between individual employees and their employers. For 57 percent of employees, agreements determine total labor cost increases at the firm level, whose allocation within the firm is negotiated locally. Finally, for 7 percent of

A central question for this paper is to what extent local wage bargaining between workers and employers primarily resembles a bargaining protocol in Cahuc et al. (2006) that renders pay responsive to outside options or whether it instead serves as a mechanism to differentiate pay by worker ability. Even when collective agreements allow for individualized wage-setting, they often entail provisions stipulating that pay should be transparent, predictable and tied to objective criteria. For example, white-collar agreements tie individualized pay to competence and performance (Medlingsinstitutet, 2021). In many collective agreements, unions support and advise workers in local wage reviews that form the basis for individualized pay, ensuring that meritocratic procedural norms are upheld (Granqvist and Regnér, 2008).[9] While there exists substantial scope for Swedish firms to differentiate wages individually based on workers' ability, and to compete with other firms in the labor market through the choice of wage policies, collective bargaining likely contributes to low wage dispersion.

Employment Protection The Swedish labor market combines comparatively strict protection of open-ended employment with relatively flexible regulation of fixed-term contracts (Skedinger, 2018; Berglund et al., 2023). This asymmetry mirrors the dual structure of many European labor markets, in which protected open-ended jobs coexist with a more flexible fixed-term tier (Boeri, 2011; Schoefer, 2025). Fixed-term contracts may expire without the employer satisfying the dismissal requirements that apply to ongoing open-ended contracts. Open-ended employment may also be preceded by a probationary period of at most six months, during which ordinary dismissal protection does not apply; unless terminated, the contract subsequently becomes open-ended (Saez et al., 2026). Within open-ended employment, dismissal costs can increase further with tenure through longer statutory or collectively agreed notice periods (Cederlöf et al., 2025), seniority-based last-in-first-out rules governing redundancies (Heyman and Skedinger, 2016; Cederlöf, 2024), and, in some cases, negotiated severance payments (Saez et al., 2026). Figure A.13 illustrates these differences: quarterly transitions into unemployment decline sharply with tenure, particularly during the first year, and the gradient is substantially attenuated after accounting for contract types.

3.2 Data

The main data source in this paper is the Labor Force Survey (LFS), a nationally representative survey on individuals' labor market status and job search activities, covering a 0.4 percent subsample of the Swedish population between ages 15 and 74. The survey is available for each year from 2005 to 2020. The LFS is a rotating panel in which individuals are sampled for up to eight consecutive quarters, and collects information about individuals' job search activity regardless of labor market status. Specifically, respondents are asked whether they have searched for another job or additional work in the past four weeks and which channels, such as contacting the public

employees (18 percent in the private sector), wages are determined through central agreements.

[9] Surveying members of the Swedish Municipal Workers' Union (*Kommunal*), Lapidus (2015) finds that one-fifth had never discussed pay with a manager and one-third had not done so in the preceding year, despite provisions for individual wage negotiation.

employment service or visiting online job boards, were used. Moreover, respondents engaged in on-the-job search are asked about the main reason for seeking new jobs.

I match the LFS to several other administrative data sets. Two data sets are of particular importance. First, RAMS contains information on the universe of matches between employers and employees between 1985 and 2020. RAMS records annual earnings and the number of months worked by an individual at a given employer.[10] Starting in 2019, RAMS provides information on earnings at the monthly level. Second, I obtain annual income statement and balance sheet data, collected by the Swedish Tax Agency and administered by Statistics Sweden, for all firms active in Sweden between 2005 and 2018. All firms are required to report this information, even though not every item is relevant for tax purposes. Lastly, I obtain a variety of information such as educational attainment, family characteristics, and distance to the workplace, from remaining administrative registers.

To compile supplementary evidence on the offer distribution faced by workers, I draw on the universe of job advertisements published between 2006 and 2025 on *Platsbanken*, a nationwide vacancy board operated by the Swedish Public Employment Service (*Arbetsförmedlingen*) and Sweden's largest job-search website. Moreover, I use longitudinal data from the UK-HLS to provide corroborating evidence on match quality dynamics.

3.3 Sample Construction

I restrict the analysis to individuals between ages 20 and 64 with stable attachment to the labor market. I exclude individuals who report studying as their main activity and workers in employment arrangements for which attachment to a particular employer is especially weak. In particular, I exclude on-call workers without an agreed work schedule and workers reporting short-term, subsidized, or other special employment arrangements. I retain workers on standard permanent and temporary contracts, including probationary, fixed-term, seasonal, project-based, and hourly employment with a predetermined work schedule. The main analysis additionally requires that the worker's employer can be assigned a meaningful measure of firm productivity. I also exclude public-sector employers and one-person firms. Following Friedrich et al. (2019), I exclude industries in which value added is not well defined or not economically comparable across firms. These restrictions define the baseline population used throughout the empirical analysis; additional restrictions required for the construction of individual firm rankings are described below.

The LFS contains personal identifiers that allow me to observe individuals in both the survey and administrative registers. Because the LFS is a quarterly survey, and RAMS is an annual-level data set, identifying primary employers for the survey population is not straightforward in cases when individuals report multiple employers in a given year. To identify primary employers in RAMS, I leverage the fact that the LFS asks respondents about the year and month in which they

[10]The main employer for a given worker is the employer from which she derives the highest annual earnings. An obvious drawback of this earnings measure is that it partially captures hours variation in addition to wage variation. I deflate earnings to 2010 levels using the Swedish Consumer Price Index, and winsorize monthly earnings at the 99.9th percentile.

started working for their primary employer. More details on the exact procedures used to link LFS and RAMS can be found in Appendix Section A.1.

Firm rankings are constructed on a separate administrative sample. I construct an annual panel consisting of all individuals aged 20 to 65 working in Sweden between 2005 and 2020, subject to several restrictions. I restrict the sample to full-time workers, which I define using the earnings threshold in Nekoei et al. (2024). The thresholds are constructed using the lowest wage observed among full-time workers in the Wage Survey for a given set of demographic characteristics (educational attainment, gender, age and immigration status).[11] I drop observations with missing information on education, industry affiliation and days spent in unemployment in a given year.

3.4 Descriptive Statistics

In this section, I provide a basic overview of job search behavior among Swedish workers. Table 1 presents summary statistics for the analysis sample and all workers surveyed in the Labor Force Survey. In the analysis sample, 6.4 percent of Swedish workers reported searching for a job in the past four weeks. Active search is strongly associated with subsequent employer mobility. A supplement to the LFS asks new hires whether their new job arose from contact initiated by the worker, or from an unsolicited offer made by the firm. As shown in Figure 1a, about one-third of matches arose from an unsolicited offer, suggesting that the largest share of matches required active search effort on the side of the worker. Figure 1b shows the share of workers transitioning to another employer over the course of the next quarter conditional on whether they actively engaged in search in the last four weeks. Among workers searching for a job, 12.0 percent work at another employer in the following quarter. In comparison, only 1.6 percent of those not searching report an employer transition.

Why does the average worker search? Table 1 reports reasons for active job search. Only 8 percent of Swedish workers looking for a job cite higher pay as the main reason for search activity, consistent with low frictional wage dispersion. Roughly one in four job searchers cites risk of losing one's job (14.7 percent) or the desire to increase working hours (10.7 percent) as the main reason for job search, underscoring the importance of hours constraints (Lachowska et al., 2026) and job security (Jarosch, 2023) as determinants of labor mobility. The most frequently cited reason is "Wanting to try something new". I interpret this motive as reflecting a preference for variety across jobs, a claim I investigate in greater detail in Section 4.

A significant share of workers cite working conditions as primary reasons for search. Around 2.3 percent of job seekers state the current job is too demanding, and 3.7 percent report searching for better working hours arrangements. A large share of respondents choose the third response: *Other reasons related to working conditions (e.g. job content, commuting)*. To better understand the difference

[11] For a subset of the workforce, one can contrast wages reported in the Wage Survey against monthly earnings. The R-squared of a linear regression of monthly earnings on the hourly wage is 0.81. Restricting the sample to employees who work exactly one hundred percent of full-time equivalent hours at the time of the survey increases the R-squared to 0.84. Hence, the extent to which variation of hours worked introduces noise in the measurement of wages using monthly earnings appears limited.

between these three amenity-related search motives, I exploit information on work conditions. As shown in Appendix Table A.2, self-reported statements about psychological and physical demands of the job strongly predict search motivated by job demands relative to other motives. On the other hand, unfavorable hours arrangements, such as shift work and regularly working at night, strongly predict search for jobs with better working hours. Commuting distance and adverse social relations at the job (conflict with colleagues, and a negative view of superiors) strongly predict search due to *Other Reasons*. I therefore interpret this last category as capturing more idiosyncratic, non-pecuniary valuations of the current job, as opposed to firm amenities that are valued by all workers.

3.5 Ranking Firms

A central object in the empirical analysis is a firm's position in the job ladder. I construct two alternative rankings that capture different dimensions of employer quality. For the main analysis, I rank firms at the national level and consider rankings within alternative definitions of labor markets in the robustness analysis. First, I use a pay-based ranking, which provides a benchmark for search models in which wages order otherwise comparable jobs (Christensen et al., 2005). To distinguish differences in employer pay policies from differences in worker composition, I construct firm pay premia using the wage decomposition in Abowd et al. (1999). Specifically, I decompose log monthly earnings of individual i at time t, denoted by w_{it}, into four components:

$$w_{it} = \alpha_i + \psi_{J(i,t)} + \mathbf{X_{it}}'\beta + \epsilon_{it} \tag{10}$$

where α_i is an individual fixed effect, $\psi_{J(i,t)}$ is a firm fixed effect, X_{it} is a set of time-varying controls – a cubic polynomial in age interacted with gender and education, a gender-specific indicator for having a child below the age of five, and year fixed effects – and ϵ_{it} is a residual innovation satisfying exogeneity conditions. To reduce noise in the estimated firm effects, I apply an empirical-Bayes shrinkage procedure to firm fixed effects before ranking firms. The resulting firm-pay ranking provides a natural starting point for the analysis as it maps closely into canonical wage-posting models of the job ladder (Burdett and Mortensen, 1998), and facilitates comparison with recent work relating worker search behavior to firm pay premia (Caldwell et al., 2025).

As a second ranking, I use value-added per worker. Value-added per worker has been used to measure employer quality in Lamadon et al. (2022). While a variety of studies finds that higher productivity firms offer higher wages, an advantage of the balance sheet data is that variation in firm pay premia may reflect compensating differentials (Lamadon et al., 2022; Morchio and Moser, 2026). As a robustness check, I use a revealed preference measure of employer quality building on a firm's hiring composition developed in Bagger and Lentz (2019), and rank firms by the share of hires recruited from other employers. In a standard wage-posting model, this share increases with employer quality because employed workers are more selective than unemployed workers (Burdett and Mortensen, 1998). Poaching shares are noisy for firms with few hires, a concern I partly address using Beta-Binomial shrinkage.

4 Empirical Results

4.1 Search Along the Job Ladder

I begin by examining whether workers' search behavior differs systematically with their current position in the job ladder. Figure 2 plots the incidence of active on-the-job search against the current employer's position in two alternative firm rankings. The first ranking is based on the firm's pay premium, the second leverages value-added per worker. Search declines across both rankings, consistent with the basic prediction of job-ladder models that workers at more desirable employers have less to gain from outside offers and therefore lower incentives to search. The gradient with respect to pay is notably modest. Moving from the bottom to the top of the firm-pay distribution is associated with a 1.1 percentage point decline in the probability of search. Translated into levels, a 10 percent increase in the firm pay premium reduces on-the-job search by only 0.23 percentage points. In contrast, the corresponding gradient with respect to value-added per employee is significantly steeper at 4.7 percentage points. Thus, workers' on-the-job search varies substantially more across firms ranked by labor productivity than across firms ranked by the pay premia they offer.[12]

Table 2 shows that the gradient is robust to the inclusion of demographic controls. The estimated slope is largely unaffected by controlling for demographic characteristics, family structure, municipality-by-year fixed effects and calendar-month fixed effects. I next examine whether differences in employment security and access to desired working hours account for part of the observed search gradients. Columns (3) and (4) of Table 2 investigate to what extent contract provision and hours constraints impact the relationship between firm ranks and search. Column (3) shows that adding controls for permanent, probationary, and fixed-term contracts reduces the firm-pay-rank coefficient from 1.1 to 0.5 percentage points and the value-added-rank coefficient from 4.7 to 3.8 percentage points. Flexibly controlling for the number of additional hours a worker would like to work renders the firm-pay gradient statistically and economically indistinguishable from zero. Differences in hours mismatch also attenuate the value-added-rank gradient. Nevertheless, even after controlling for contract type and hours mismatch, the gradient with respect to value added remains sizable at 2.5 percentage points. Taken together, these findings suggest that employer quality is strongly tied to the provision of stable, full-time employment.

These results suggest that firm pay premia incompletely capture the dimensions of employer quality relevant for search. Appendix Figure A.2a shows that in the Swedish Work Environment survey (AMU), value-added rank is strongly associated with reported job satisfaction, whereas the relationship with firm-pay rank is weak. I leverage information on working conditions to assess whether this discrepancy is driven by compensating wage differentials. For each surveyed worker, I compute the difference between her employer's value-added rank and its pay rank and regress it on characteristics of the current job, controlling for observables. A positive difference means that the employer ranks higher in value added than in pay, so a positive coefficient indicates that

[12] Appendix Figure A.1 relates firm pay premia to productivity and compares search gradients with respect to observed pay premia and pay premia predicted by productivity.

the work condition is more common at firms that pay less than their productivity rank would imply. Long commutes and irregular working arrangements predict a lower rank difference, while working from home and opportunities for employer-provided training predict a higher one (Figure A.2b). Subjective workplace characteristics show a similar pattern: meaningful work, enjoyment of work, supportive supervisors, and flexible schedules are associated with higher rank differences (Figure A.2c). Firms offering better amenities thus pay less than their productivity rank would imply, consistent with compensating wage differentials.

While the share of individuals engaging in search declines along the job ladder, it is possible that further reductions in search effort arise at the intensive margin. Appendix Table A.10 presents the estimated slope of two measures of the intensive margin of search, the number of search methods, as well as the search duration in weeks, with respect to the value-added rank. I estimate the model among active searchers to isolate the intensive margin of search. The estimated model implies that moving from the lowest-ranked to the highest-ranked firm reduces the number of search methods used by 0.49 relative to a sample mean of 2.1. While this result suggests that workers adjust search behavior along the job ladder beyond the decision to search or not, the magnitudes imply that substantial search effort is still exerted at the highest-ranked firms.[13]

I examine whether the estimated search gradients are sensitive to the definition of labor markets and employers. Appendix Table A.8 replaces national firm rankings with rankings within municipalities, 2-digit industries, and labor markets identified through flow-based clustering (Nimczik, 2017; Berger et al., 2024). The gradients are largely unchanged for municipal and flow-based markets, although the productivity-rank gradient becomes less steep within industries, declining in magnitude from 4.7 to 3.1 percentage points. Appendix Table A.7 compares firm- and establishment-level rankings based on pay premia and poaching shares. The resulting search gradients are similar, suggesting that aggregation across establishments does not substantially attenuate the estimated relationship.[14] Together, these checks show that the negative search gradient persists under more granular definitions of both labor markets and employers. Active search declines along the job ladder, but remains to a large extent even among workers at the highest-ranked firms. I next examine their reported motives to understand why workers continue to look for other jobs.

[13]Appendix Figure A.12 shows that all forms of search methods, ranging from information acquisition via reading newspapers or job ads to direct employer contacts, become less frequent moving up the job ladder. However, conditional on searching, direct employer contacts become slightly more frequent while the incidence of reading about openings declines. Hence, while the number of methods declines overall, its composition shifts to slightly more effective measures.

[14]The unit of analysis also changes the number of fixed effects estimated and therefore potentially impacts the precision of the estimated fixed effects. To rule out that differential precision in the independent variable obscures differences between firm- and establishment-level analyses, I truncate the tails of each rank distribution, and alternatively require at least six hires over an eight-year window. These restrictions induce varying changes in the estimated slope, but leave the relative difference between firm- and plant-level analyses largely intact.

4.2 Motives Across the Job Ladder

Having established that workers search across the distribution of firms, and that search motives contain meaningful information about the nature of mobility, I now examine how motives vary across the job ladder.

Figure 3 reveals that there is substantial variation in motives for on-the-job search across the job ladder. At the lower rungs, the desire to adjust hours constitutes a major reason for on-the-job search. Almost all respondents in this category state the desire to increase hours as the primary reason for search. Similar to hours adjustments, search due to anticipated layoff or contract expiration accounts for around 20 percent of on-the-job search at the lowest rungs.[15] Notably, the contribution of involuntary search declines over the job ladder down to 10 percent of search in the top-decile. This finding is consistent with the job ladder exhibiting "slippery" bottom rungs as highlighted in Jarosch (2023). Neither hours adjustments nor involuntary search due to anticipated job destruction can explain why workers continue to search in the highest-ranked firms.

In the top-decile, more than 40 percent of search is accounted for by respondents who report wanting to try something new as the primary reason for their search. The rising share of this motive reflects the decline of other motives rather than an increase in its own incidence. The incidence of active on-the-job search primarily due to this reason is approximately constant across the productivity distribution, as seen in Appendix Figure A.11. Two pieces of evidence suggest that the motive reflects idiosyncratic valuations of a particular match. First, Appendix Figure A.6a shows that among workers who change employers, those who searched for higher pay, a better use of their training, or more hours move to firms ranked about 3 to 8 percentile points higher than those who searched to try something new, while those who anticipated job loss move to firms ranked about 2 to 3 points lower. Moves motivated by the desire to try something new thus lie between upward moves driven by pay and hours and downward moves driven by job loss. Second, the motive lines up with how workers describe their work: Appendix Figure A.9 shows that workers who perceive their work as monotonous are significantly more likely to search to try something new, consistent with a taste for variety. Lentz et al. (2023) argue that preference heterogeneity is essential to explain (downward) mobility across the distribution of firms.

In order to shed light on how reasons to search map into mobility, I first estimate the mobility yield associated with each search motive. This is the difference in the probability of changing employers over the following quarter relative to not searching, conditional on individual and firm fixed effects and demographic controls. I then compute the composition of motives weighting each observed motive by its estimated mobility yield, reported in Column (3) of Appendix Table A.5. Column (7) of Appendix Table A.11 presents the results. While risk of job loss accounts for around 11.8 percent of search at the top-decile of firms, differential mobility across motives implies that it accounts for almost 19.5 percent of mobility, consistent with workers strongly lowering their reservation wage. Meanwhile, the weighting implies that workers who search to try something

[15] Appendix Figure A.7 reports search motives by contract type and hours mismatch, together with the relationship between hours mismatch and search incidence.

new account for 43.7 percent of all searchers at the top-decile, but only 33.8 percent of mobility. Nevertheless, idiosyncratic motives account for the majority of mobility at top-decile firms.

Finally, Appendix Table A.11 shows that the composition of motives is robust to controlling for worker characteristics and using alternative firm rankings. Column (3) shows that controlling for worker observables lowers the share of searchers motivated by the desire to try something new from 43.7 to 39.5 percent. Panels b) and c) of Appendix Table A.11 show that the dynamic composition of search motives is unaltered when firms are ranked based on firm pay or poaching shares. For example, search motivated by the desire to try something new accounts for 20.8 percent at the bottom decile of the firm ladder and 45.2 percent at the top-decile, closely mirroring the figures obtained under the baseline ranking.

4.3 Persistence and Concentration of Search

Having shown that search varies across firms and often reflects idiosyncratic motives, I now examine how it is distributed across workers at similarly ranked firms. A low search rate in cross-section does not, by itself, establish persistent differences in workers' incentives to seek outside options. With independent, transitory shocks to search costs, for example due to fluctuations in hours worked, otherwise identical workers could each search occasionally when their costs are low, generating the same cross-sectional search rate. Persistent differences in gains from search would instead concentrate repeated observations of search among a smaller group of workers. I exploit the panel dimension of the LFS to distinguish these patterns by examining how search is distributed across workers over time.

Figure 4a compares the share of workers searching at the first interview with the share observed searching at least once across eight quarterly interviews. Workers are grouped by the productivity decile of their employer at the first interview. Within each decile, I compare the observed cumulative share with a benchmark in which search is independent across interviews, holding fixed the observed search rate at each interview.[16] The comparison therefore sheds light on excess concentration of search beyond that implied by differences in average search rates across initial employer ranks.

Across the employer distribution, only about one-fifth to one-quarter of workers are observed searching at least once, substantially fewer than under independence. Among workers initially employed in the bottom decile, approximately 25 percent are observed searching, compared with 40 percent under the independence benchmark. In the top decile, the corresponding shares are approximately 21 and 31 percent. Repeated observations of active search therefore disproportionately come from the same workers. This concentration is present throughout the employer distribution, including among workers initially employed at the highest-ranked firms.

These results are consistent with a persistent attachment of workers to their employers which

[16] Let p_{dk} denote the search rate at interview k among workers whose employer at the first interview belongs to productivity decile d. The independence benchmark is $1 - \prod_{k=1}^{8}(1 - p_{dk})$. Each interview records search during the preceding four weeks, so the cumulative measure captures search in these eight reference windows.

reduces their incentive to generate outside options. I next examine how search varies with employer tenure and changes within continuing employment relationships to shed light on the persistence and evolution of attachment.

4.4 Tenure and Match Dynamics

Between-Spell The preceding results suggest that workers' search is to a large extent motivated by idiosyncratic factors beyond a firm's overall quality. In order to understand whether workers sort into jobs with higher persistent match quality, I use employer tenure as a proxy for match quality. Workers who value their current match highly have less to gain from switching firms and are therefore more likely to remain, so long-tenure matches should be selected toward stronger attachment. To distinguish sorting from life-cycle changes in search costs, I apply an age correction following Engbom et al. (2026), using the search profile of workers recently hired out of unemployment. Controlling for age in a regression model does not identify the genuine life-cycle effects correctly, as match quality may increase through past search and mobility. Under the assumption that the unemployed accept all offers, match quality among recent hires is treated as invariant with age, allowing identification of the life-cycle profile of search.[17]

Figure 4b shows that on-the-job search declines substantially with employer tenure even after adjusting for the life-cycle profile of search. The search rate falls from approximately 9.1 percent among workers in the first year of the employment spell to around 5.4 percent after ten years, before stabilizing at approximately 3.1 percent among workers with more than twenty years of tenure. The decline is concentrated early in the employment relationship but continues beyond the first year. Matches with high tenure are associated with substantially lower search, although active search remains present even in employment relationships that have lasted several decades. Appendix Figure A.11b plots the dynamic composition of on-the-job search by primary motive. While risk of job loss and underemployment account for a large share of searchers in low-tenure matches, their prevalence in long-run matches is negligible. Instead, other reasons regarding working conditions and the desire to try something new account for around 60 percent of search among workers in matches lasting more than 20 years. Search in durable matches is therefore largely voluntary, driven by non-pecuniary considerations rather than job insecurity or hours constraints.

Compared to search at the top-ranked firms, the incidence of on-the-job search in long-tenure jobs is markedly lower, suggesting that workers can sort into jobs with high match quality via other means than moving to better firms. In order to understand the potential mechanisms of sorting, I compare workers with more than ten years of tenure against workers with less than ten years of tenure conditional on each firm decile. Figure 4c plots the difference in search between the two

[17] Between ages 20 and 50, search remains remarkably stable, declining only from 16 to 15 percent. The decline then accelerates rapidly after the age of 50, falling to around 7.5 percent by the age of 60. Appendix Figure A.3 contrasts the estimated life-cycle profile among the employed against the life-cycle profile of the search intensity among unemployed job seekers, as measured using the number of search methods. In line with previous work in Aguiar et al. (2013), unemployed search exhibits a hump shape, increasing sharply between ages 20 and 25, remaining stable throughout mid-life, and falling rapidly after the age of 50. Reassuringly, except for the initial increase in search, the profile among the employed tracks the unemployed profile closely.

groups for each motive.[18] Longer-tenure workers search less throughout the firm distribution, although the difference narrows substantially with firm rank: the gap is approximately 6.3 percentage points in the bottom decile and 3.6 percentage points in the top-decile. The composition of this gap between high and low tenure workers also changes along the ladder. At lower-ranked firms, risk of job loss and the desire to increase working hours explain most of the lack of search among high-tenure workers. At higher-ranked firms, these motives become much less important, while wanting to try something new and other reasons related to working conditions account for a larger share of the difference. These patterns are consistent with workers sorting on employment stability and access to desired working hours at the bottom of the firm distribution, and along more idiosyncratic dimensions of match quality at the top.

Within-Spell The tenure gradient in Figure 4b is a cross-sectional relationship and may reflect both selection across matches and persistent differences in workers' propensity to search. Whether search also changes within the same employment relationship is a separate question. Since the LFS repeatedly surveys individuals and asks about the reason for search at each interview, the data allow me to distinguish changes over the life of a match from differences across matches. Specifically, for each search outcome r, I estimate

$$s_{it}^{r} = \alpha_{ij}^{r} + \beta^{r} T_{it} + \varepsilon_{it}^{r}, \tag{11}$$

where s_{it}^{r} is an indicator for search outcome r, T_{it} denotes tenure in years with the current employer, and α_{ij}^{r} denotes an employer-spell fixed effect. Employer-spell fixed effects absorb persistent differences in the propensity to search due to specific motives across matches. I consider three outcomes: any active on-the-job search, search motivated by the desire to try something new, and search for all other reasons. Since duration is itself an outcome of search, I restrict the sample to *failed* searchers who are at least 12 months away from the completed spell duration at the time of the interview.

Figure 4d depicts estimates with and without spell fixed effects. The cross-sectional relationship reproduces the pattern in Figure 4b: an additional year of tenure is associated with a 0.15 percentage point decline in the probability of on-the-job search. This decline is entirely accounted for by motives other than wanting to try something new. Search motivated by the desire to try something new slightly increases in tenure. Within employer spells, the relationship reverses. An additional year of tenure is associated with a 0.65 percentage-point increase in the probability of active search. Search motivated by the desire to try something new increases by 0.50 percentage points per year, accounting for approximately three quarters of the aggregate increase. Search for all other motives also increases, but by a smaller amount of 0.16 percentage points per year. Both components are statistically distinguishable from zero.

In order to assess the sensitivity of the results to the survivorship restriction, Figure A.4b varies the exclusion horizon relative to the eventual end of the employer spell. The aggregate

[18] Appendix Figure A.10 extends this comparison to more granular breakdowns of tenure.

tenure gradient becomes smaller as observations closer to separation are excluded. Nevertheless, the coefficient on search motivated by wanting to try something new remains positive at longer horizons, while the contribution of other motives becomes small or negative. The increase in search for this reason is therefore not confined to observations immediately preceding the eventual separation.[19] Panel c) raises the minimum number of usable interviews within a spell from two to eight. The coefficient remains positive, demonstrating that the pattern is not driven by spells with short observed histories where fixed effects are uninformative. In addition, Appendix Table A.3 shows that this result is robust to a variety of alternative specifications and sample restrictions, such as adjustments for the life-cycle profile, selecting individuals with a permanent contract, who are unlikely to exhibit contractual changes over the spell, and estimating the model in first differences as opposed to fixed effects.

Taken together, the cross-sectional and within-spell evidence highlights two offsetting forces. Across workers, higher-tenure matches exhibit lower search, consistent with sorting based on persistent heterogeneity in match quality. At the same time, within continuing matches, the propensity to search increases as tenure accumulates, with the largest contribution coming from the desire to try something new. This pattern is consistent with a dynamic component of match value that may render otherwise durable employment relationships less attractive over time, particularly along idiosyncratic, non-pecuniary dimensions.

4.5 Job Satisfaction Over the Spell

The preceding results suggest that the propensity to search can increase within otherwise durable employment relationships, driven by a stated desire for reset as opposed to dissatisfaction with pay. To provide complementary evidence on how workers value ongoing matches, I study the dynamics of job satisfaction around employer transitions. I utilize the Swedish Work Environment Survey (AMU), a biennial supplement to the LFS, between 1998 and 2021. The general nature of the question: "How satisfied are you with your job?" justifies its use as a proxy for utility. From the matched employer-employee data, I can reconstruct start and end dates of a job spell, and thus observe job satisfaction through the randomness of the interview date of the AMU at different points in the life-cycle of a job.

I restrict the analysis to direct employer-to-employer transitions in which both the origin and destination employers lie in the analysis sample: neither employer is in the public sector, a one-person firm, or an excluded industry. Each AMU response is attached to the employer identified in the respondent's first qualifying fourth-quarter LFS observation in the same year and matched to an administrative employment spell covering the survey month. I use the recorded spell dates to

[19] Panel b) also compares two ways of imposing the survival restriction. The interview-specific rule retains observations sufficiently far from separation, allowing a spell to contribute earlier but not later interviews. The fixed-cohort rule instead requires the spell to survive beyond the eighth LFS interview plus the indicated horizon, keeping survival-based eligibility fixed across the sequence of interviews. The positive gradient in search motivated by wanting to try something new persists under both rules.

construct event time over approximately four years on either side of an employer transition. [20]

I group monthly event time into six-month intervals and then estimate the following linear regression:

$$v_{it} = \sum_{\substack{k \in \mathcal{K} \\ k \neq -4}} \beta_k \, \mathbf{1}\{b_{it} = k\} + X_{it}'\gamma + \lambda_t + \varepsilon_{it}, \tag{12}$$

where v_{it} denotes the job satisfaction of worker i interviewed in calendar month t, and $b_{it} = \lfloor d_{it}/6 \rfloor$ denotes the six-month bin containing monthly event time d_{it}, with $\mathcal{K} = \{-8, \ldots, 8\}$. The vector X_{it} includes education–gender-specific intercepts and cubic polynomials in age, while λ_t denotes calendar-year-by-month fixed effects. The omitted category corresponds to event months -24 through -19 and is plotted at -2 years. Each coefficient β_k therefore measures the difference in job satisfaction between event-time bin k and this reference interval, adjusted for observable worker characteristics and calendar time.

Figure 5a shows job satisfaction around employer transitions. Initially, job satisfaction remains flat over time, but decreases rapidly during the two years prior to the end of a job spell. Following the transition, job satisfaction rises sharply. Since the pattern reflects cross-sectional variation, it cannot be interpreted as depicting within-spell dynamics of job satisfaction without additional assumptions on selective attrition. If job spells are characterized by permanent differences in match value, low value jobs may end sooner and are therefore unlikely to be observed long prior to separation. In order to address this concern, I restrict the sample to observations where the origin employment spell lasts at least four years, using completed duration as a proxy for the permanent component of match quality. As can be seen in Figure 5a, this completed duration restriction has a limited influence on the estimated pre-transition profile of job satisfaction. Given that the reduction in satisfaction takes place sufficiently prior to the end of a spell, the timing is consistent with workers having sufficient scope to respond through active on-the-job search before moving.

A key limitation of the AMU is that it only allows for a cross-sectional analysis. In order to provide further evidence on dynamics of match quality, I supplement the analysis using data from the UK Household Longitudinal Study (UK-HLS). Like the AMU, the UK-HLS asks respondents to rate their current job satisfaction on a Likert scale. In contrast to the AMU, the UK-HLS has a larger sample size and a panel structure, allowing me to control for persistent differences in reported job satisfaction across workers. Figure 5b shows that the cross-sectional estimation strategy applied to the UK-HLS data implies a similar decline in job satisfaction around the employer transition. Moreover, the pattern remains robust when including individual fixed effects, suggesting that permanent worker heterogeneity cannot account for the dynamic profile. Figure 5b shows that the same pattern is replicated by a difference-in-differences design comparing observationally similar workers with similar levels of job satisfaction 18 months prior to the transition.

Previous work has shed light on firm-level shocks as drivers of labor mobility (Friedrich et al., 2019; Balke and Lamadon, 2022). In order to rule out that changes in job satisfaction dynamics

[20] Each response contributes to at most one transition. When an observation is eligible to describe both a preceding entry and a subsequent exit, I give priority to the exit.

reflect responses to standard firm-level adjustments such as cuts to wages or hours, I estimate the panel regression controlling for log hourly wages and weekly hours. As shown in Figure 5c, these controls barely affect the estimated coefficients. In addition, Appendix Figure A.5d shows that coefficient estimates remain largely unchanged when restricting the sample to transitions that are classified as voluntary based on respondents' retrospective reasons for leaving their previous employer. Taken together, the evidence suggests that changes in non-pecuniary aspects of the job drive both the deterioration in match value before separation and the improvement associated with employer mobility.

5 Model

In order to quantify the role of endogenous on-the-job search in the labor supply facing firms, I develop a random search model in which workers choose whether to search and whether to accept outside offers. In line with the reduced-form decomposition of search motives, I allow jobs to differ in pay, hours mismatch, and contract type, while match-specific amenities are persistent but can change over the course of an employment relationship. Because the same amenities govern whether a worker accepts an outside offer and whether it pays to search for one, preferences shape both margins of retention. I use this framework to quantify the contribution of endogenous search to firm labor supply and how this contribution depends on heterogeneity in non-pecuniary match value.

5.1 Environment

States and timing. Time is discrete and measured in months. The worker's state has three components. The first is her education e, which determines her human capital and offer distribution. The second consists of job characteristics that remain fixed throughout a match: the firm's rank on the job ladder $y \in [0,1]$ and hours mismatch $h \in [0,1]$. The third consists of characteristics that evolve within a match: the contract state $j \in \mathcal{J} = \{P, B, F, N\}$, which distinguishes permanent, probationary, and fixed-term employment as well as advance notice of layoff; the duration d in the current contract state, as opposed to total tenure with the employer; and the match-specific amenity q. I collect the worker and job characteristics in $\mathbf{x} = (e, y, h, j, d, q)$.

Each month, workers observe their current state and draw search-choice shocks. They then choose whether to search, which determines their offer-arrival probability. Workers receive current payoffs net of search costs and may then leave the labor market. Those who remain decide whether to accept any offer received; workers who accept begin the next period in the offered job. If no offer is accepted, separation risk is realized: workers who separate enter unemployment next period, while retained matches undergo contract and amenity transitions.

Preferences. Workers discount the future with factor β and leave the labor market with probability μ each month. An employed worker in state $\mathbf{x}$ receives the flow payoff

$$u(\mathbf{x}) = a(e)\,\psi(y)\,(1-h) + q, \tag{13}$$

where $a(e)$ is an education-specific ability shifter and $\psi(y)$ is the pay premium of a firm at rank y. Hours mismatch reduces earnings proportionally, and the match-specific amenity q enters additively, so that amenities, like search costs below, are measured in units of earnings. Each component corresponds to a search motive in the data: pay to search for higher wages, hours mismatch to search for different working hours, and the amenity to idiosyncratic, nonpecuniary motives. The contract state does not enter flow payoffs; it affects search through separation risk, which generates search in anticipation of job loss.

Search technology and offer distribution. Search is random. Each month, a worker receives an offer with probability $\lambda(s)$, which depends on her current search action $s \in \{0, 1\}$. Throughout the paper, I assume a linear offer technology:

$$\lambda(s) = \lambda_0 + \lambda_1 s, \tag{14}$$

where λ_0 is the probability of receiving an unsolicited offer and $\lambda_1 \geqslant 0$ is the return to active search, i.e., the increase in the offer arrival probability from searching, with $\lambda_0 + \lambda_1 \leqslant 1$. Searching incurs a per-period cost κ, whether or not an offer arrives. Because search is a binary choice, κ acts as a fixed cost: a worker searches only if the expected gain from the additional offers exceeds κ, up to a transitory shock specified below. While I assume that search costs are identical for employed and unemployed workers, I follow Faberman et al. (2022) and Nekoei et al. (2024) in allowing the effectiveness of search to differ by labor force status. The unemployed therefore face their own offer arrival function, $\lambda^u(s_u) = \lambda_0^u + \lambda_1^u s_u$.

Conditional on receiving an offer, the worker meets a private-sector firm with probability ϕ_e and a public-sector employer with probability $1 - \phi_e$. I refer to these as the ranked, or inside, sector and the outside sector, respectively. Ranked-sector offers $\hat{\mathbf{x}}$ are drawn from an education-specific distribution $F(\hat{\mathbf{x}} \mid e)$. This specification imposes two assumptions. First, the offer distribution is independent of the search action, so search affects only the probability of receiving an offer. Second, employed and unemployed workers face the same offer distribution, which allows hires from unemployment to reveal it.

Workers move to the outside sector from all parts of the firm distribution. To capture this without modeling heterogeneity within that sector, I allow employed workers' decisions over outside-sector offers to depend on transitory taste shocks. Each alternative $a \in \{0, 1\}$, accepting or staying, carries a shock $\sigma_O \eta_a$, where $\sigma_O > 0$ is a scale parameter and (η_1, η_0) are type-I extreme-value draws, i.i.d. across alternatives, workers, and periods. I use the location–scale normalization

$\eta_a \sim \text{Gumbel}(-\gamma, 1)$, where γ is the Euler–Mascheroni constant, so that $\mathbb{E}[\eta_a] = 0$.[21]

Contracts. Contract states generate separation risk and thereby search in anticipation of job loss. Probationary and fixed-term contracts expire after D_j months, $j \in \{B, F\}$; at expiry, they end in separation, conversion to permanent employment, or, for fixed-term contracts, renewal. Permanent workers receive advance notice of layoff with monthly probability ξ_N and, unless they have moved to another job in the meantime, separate when the notice period of D_N months expires. Let $\delta(\mathbf{x})$ denote the probability of involuntary separation when no outside offer is accepted, and let Π^J denote the transition probabilities over contract states and elapsed duration d, conditional on the match continuing. Appendix Section E specifies these transition probabilities.

Match-specific amenities Each newly offered job comes with an independent match-specific amenity drawn from a mean-zero Gumbel distribution F^q with standard deviation σ_q. Within an ongoing employment relationship, the amenity remains unchanged with probability $1 - \zeta$ and is independently redrawn from F^q with probability ζ each month. Conditional on retaining the current employer, the transition kernel is therefore

$$\Pi^q(dq' \mid q) = (1 - \zeta)\delta_q(dq') + \zeta F^q(dq'), \tag{15}$$

where δ_q denotes a point mass at the current amenity. The parameter ζ governs how often match-specific amenities change: $\zeta = 0$ corresponds to permanent match amenities, whereas $\zeta = 1$ implies independent potential amenity realizations in consecutive periods. Amenities are the model's main source of persistent attachment, aside from initial promotions into permanent contracts. A worker who draws a high q has little reason to search or to accept outside offers and remains attached until the amenity is redrawn. Because surviving matches are selected on high amenities, a redraw lowers match-specific amenities on average, even when firm rank and hours mismatch remain fixed, and can therefore induce renewed search in otherwise durable matches. The same amenity process applies to employment in the outside sector.

5.2 Worker's Problem

I describe the worker's problem in three steps: the value of continuing in the current match, the gain from an offer, and the search decision.

Continuation following no accepted offer. Let $\Pi(d\mathbf{x}' \mid \mathbf{x})$ denote the transition kernel induced jointly by the contract process Π^J and the amenity process Π^q, conditional on retaining the current

[21] Equivalently, $\sigma_O \eta_a$ has location $-\sigma_O \gamma$ and scale σ_O, and therefore has mean zero. The common-location normalization does not affect the logit acceptance probabilities. It removes the additive $\sigma_O \gamma$ term from the expected maximum, which would otherwise be absorbed by the payoff and search-cost shifters.

match. If the worker does not accept an outside offer, her expected continuation value is

$$V^R(\mathbf{x}) = \delta(\mathbf{x})U(e) + \big[1-\delta(\mathbf{x})\big]\int V(\mathbf{x}')\Pi(d\mathbf{x}' \mid \mathbf{x}). \tag{16}$$

This value is the benchmark against which the worker evaluates any incoming outside offer and summarizes her attachment to the current match: it rises with pay and amenities and falls with hours mismatch and separation risk. High separation risk therefore raises the gain from any offer, which generates search in anticipation of job loss. Higher pay raises $V^R(\mathbf{x})$ and lowers the probability of accepting an outside offer.

Value of an offer. Let $\hat{\mathbf{x}} \sim F(\cdot \mid e)$ denote an offer from the ranked sector. A newly accepted contract begins with duration $d = 1$. Using $[z]_+ \equiv \max\{z, 0\}$, the expected gain conditional on receiving an offer is

$$\begin{aligned}\Omega(\mathbf{x}) = \phi_e \mathbb{E}_{\hat{\mathbf{x}}}\Big[\big[V(\hat{\mathbf{x}}) - V^R(\mathbf{x})\big]_+ \,\Big|\, e\Big] \\ + (1-\phi_e)\mathbb{E}_{\hat{q},\eta}\left[\max\left\{V_o(e,\hat{q}) - V^R(\mathbf{x}) + \sigma_O\eta_1,\ \sigma_O\eta_0\right\}\right],\end{aligned} \tag{17}$$

where $V_o(e, \hat{q})$ is the value of an outside-sector job with amenity $\hat{q}$. Ranked-sector offers carry no additional transitory taste shock, because idiosyncratic preferences enter through the amenity $\hat{q}$, which is part of the offered state. Hence, the worker accepts if and only if $V(\hat{\mathbf{x}}) \geqslant V^R(\mathbf{x})$. Outside-sector offers are accepted with logit probability $\Lambda\big([V_o(e,\hat{q}) - V^R(\mathbf{x})]/\sigma_O\big)$. The probability that an offer is accepted is therefore

$$A(\mathbf{x}) = \phi_e \Pr\big[V(\hat{\mathbf{x}}) \geqslant V^R(\mathbf{x}) \mid e\big] + (1-\phi_e)\,\mathbb{E}_{\hat{q}}\left[\Lambda\Big(\tfrac{V_o(e,\hat{q}) - V^R(\mathbf{x})}{\sigma_O}\Big)\right]. \tag{18}$$

Differentiating equation (17) gives $\partial\Omega(\mathbf{x})/\partial V^R(\mathbf{x}) = -A(\mathbf{x})$, implying that a more valuable current match lowers the gain from an offer by the probability that the offer would have been accepted. The derivative illustrates the close connection between the two retention margins — the acceptance probability determines how much the return to search falls when the current match improves.

Search decision. Let $\widetilde{\beta} \equiv \beta(1-\mu)$ denote the effective discount factor. Combining the baseline continuation value and the incremental value of an offer, the choice-specific value of search action s is

$$W(\mathbf{x}, s) = u(\mathbf{x}) - \kappa s + \widetilde{\beta}\left[V^R(\mathbf{x}) + \lambda(s)\Omega(\mathbf{x})\right]. \tag{19}$$

The decomposition in equation (19) is useful because $\Omega(\mathbf{x})$ is defined as an incremental gain. The term $V^R(\mathbf{x})$ is therefore received regardless of whether an offer arrives, while $\lambda(s)\Omega(\mathbf{x})$ captures the additional option value created by an offer.

Let the search-choice shocks be independent across alternatives and periods, with $\epsilon_s \sim \text{Gumbel}(-\gamma, 1)$ i.i.d. for $s \in \{0, 1\}$. The shocks capture transitory variation in the cost of search,

such as time constraints or circumstances outside work. Their independence serves two purposes. Because they are independent over time, they do not enter the state, so the value of employment depends only on $\mathbf{x}$. Moreover, because they generate no persistence, any correlation in a worker's search over time must come from the persistent components of her state, which allows repeated observations of search to separate persistent attachment from transitory search choices. The value of employment before search cost shocks are realized is

$$V(\mathbf{x}) = \mathbb{E}_{\epsilon}\left[\max_{s\in\{0,1\}}\{W(\mathbf{x},s) + \sigma_s \epsilon_s\}\right]. \tag{20}$$

Since search decisions affect only the offer probability and search costs, the net return to search is given by

$$W(\mathbf{x},1) - W(\mathbf{x},0) = \tilde{\beta}\lambda_1\Omega(\mathbf{x}) - \kappa, \tag{21}$$

so that the current match affects search only through the gain from an offer, and the probability of search is

$$p(\mathbf{x}) = \Lambda\left(\frac{\widetilde{\beta}\lambda_1\Omega(\mathbf{x}) - \kappa}{\sigma_s}\right). \tag{22}$$

The scale σ_s governs how sharply search changes around the threshold $\widetilde{\beta}\lambda_1\Omega(\mathbf{x}) = \kappa$, at which the net return to search is zero. Because $\partial\Omega/\partial V^R = -A(\mathbf{x})$, an increase in $V^R(\mathbf{x})$ by ΔV lowers the search probability by approximately $(\widetilde{\beta}\lambda_1/\sigma_s)\, p(\mathbf{x})[1-p(\mathbf{x})]A(\mathbf{x})\,\Delta V$. The search response to pay is therefore concentrated among marginal workers near the search threshold and weighted by the likelihood that outside offers are accepted.

Unemployed workers. An unemployed worker of education e receives flow payoff $b\,a(e)$ and remains unemployed if she does not accept an offer. Her offer-arrival probability is $\lambda^u(s) = \lambda_0^u + \lambda_1^u s$. She faces the same offer distribution, search cost, and search-choice shock scale as employed workers. Acceptance depends on continuation values, without transitory acceptance shocks. The appendix gives the Bellman equations defining the unemployment value $U(e)$.

Stationary population. I normalize the mass of workers to one. Each month, workers who leave the labor market are replaced by an equal mass of unemployed entrants with education distribution ν_e. Let ν denote their distribution over the full state space, and let Π^0 denote the transition kernel conditional on no labor-market exit. This kernel combines optimal search and offer acceptance with exogenous separations, contract transitions, and amenity changes. The stationary distribution G satisfies

$$G = (1-\mu)G\Pi^0 + \mu\nu, \qquad G\mathbf{1} = 1. \tag{23}$$

The distribution G determines the shares of workers in unemployment, ranked employment, and outside employment, as well as the composition of employed workers across firms and match states. The appendix details the transition kernel and the implied distribution of employer tenure.

5.3 Identification

The parameters fall into three groups. The first is set externally or normalized. The second—the contract kernel, the notice process, the outside sector, and the search technology of the unemployed—is identified from worker flows that are either standard or do not involve the on-the-job search decision; the arguments are collected in Appendix F. This section concentrates on the third group, the on-the-job search block: the arrival technology (λ_0, λ_1), the search cost κ, the scale of the search-choice shock σ_s, and the scale and persistence of match-specific amenities (σ_q, ζ). Recovering the response of search to pay requires separating three pairs of forces: offer arrival and the willingness to accept, persistent match value and transitory search costs, and the behavioral response of search and selection on non-pay attributes. Each identification problem is resolved by recourse to the core empirical facts documented in Sections 3 and 4: the share of hires initiated by workers, the gradient of search across firms, the persistence of search within employment spells, and search in long-tenure matches. Throughout, $\ell(p) = \ln[p/(1-p)]$ denotes the log-odds of a probability p, which turns logit choice probabilities into linear expressions.

Offer arrival versus acceptance. Searchers are substantially more likely to change employers than nonsearchers (12.02 versus 1.60 percent per quarter), as shown in Figure 1b. This gap could reflect more offers or a greater willingness to accept them. The share of hires that originate from worker-initiated contact rather than from an unsolicited approach by the firm in Figure 1a, which I call the active-hire share θ_e, separates the two. Because active and passive offers are drawn from the same distribution, the channel through which an offer arrives does not affect its acceptance. Acceptance therefore cancels from the ratio of active hires to all hires of searchers, and the fraction of offers received by searchers that search itself generates is

$$\frac{\lambda_1}{\lambda_0 + \lambda_1} = \frac{\theta_e \, \bar{f}}{p \, f(1)}, \tag{24}$$

where p is the share of employed workers who search, and $\bar{f}$ and $f(1)$ are the transition rates of all employed workers and of searchers, respectively.[22] All four objects on the right-hand side are observed in the linked data. Given this fraction, the remaining gap in transition rates reveals how much more likely searchers are to accept the offers they receive.

Match heterogeneity and the search gradient. Search declines with firm rank, but a shallow gradient could reflect noisy search costs or heterogeneous preferences over jobs. To see why the gradient alone cannot separate the two, abstract from contract dynamics and hours mismatch. The probability that a worker at firm rank y with amenity q searches actively is

$$P(y, q) = \Lambda\left(\frac{\nu(y, q) - \kappa}{\sigma_s}\right), \qquad p(y) = \mathbb{E}\big[P(y, q) \mid y\big], \tag{25}$$

[22] See Appendix Section F for further details.

where $v(y,q) = \widetilde{\beta}\lambda_1\Omega(y,q)$ is the gross return to search. The data reveal the average search rate $p(y)$ at each firm rank, which integrates over the unobserved amenities. Its variance decomposes into a component due to persistent differences in amenities and a component due to transitory search-choice shocks:

$$p(y)[1-p(y)] = \underbrace{\mathrm{Var}[P(y,q) \mid y]}_{\text{Variation across amenity states}} + \underbrace{\mathbb{E}[P(y,q)(1-P(y,q)) \mid y]}_{\text{Choice variation within amenity states}}. \tag{26}$$

Because search-choice shocks are i.i.d., the second component measures how many workers are close to the search threshold: a uniform increase in the return to search by Δv raises $p(y)$ by approximately $\mathbb{E}[P(y,q)(1-P(y,q)) \mid y]\,\Delta v/\sigma_s$. Persistent amenity differences, by contrast, move workers away from the threshold, raising the variance of search while lowering its responsiveness. Let

$$\omega(y) \equiv \frac{\mathrm{Var}[P(y,q) \mid y]}{p(y)[1-p(y)]} \tag{27}$$

denote the share of the variance of search due to differences across amenity states. Differentiating the log-odds of search with respect to firm rank gives

$$\frac{d\ell[p(y)]}{dy} = \frac{\bar{v}_y^M(y)}{\sigma_s}\big[1-\omega(y)\big] + \frac{\int_Q [P(y,q)-p(y)]\, g_y(q \mid y)\, dq}{p(y)[1-p(y)]}, \tag{28}$$

where $\bar{v}_y^M(y)$ is the average derivative of the return to search with respect to firm rank, and the last term captures differential selection into amenities across firm ranks. The average weights each amenity state by $P(y,q)[1-P(y,q)]$, the responsiveness of search in that state, and therefore places most weight on workers near the search threshold. The gradient is therefore governed by three forces: the change in the return to search relative to the scale of the search-choice shock; an attenuation factor $1-\omega(y)$, which is smaller the more search variation is due to persistent amenity differences, and sorting on amenities across firm ranks. A shallow gradient can therefore reflect a large σ_s, substantial persistent heterogeneity, or sorting, and even perfect knowledge of the return to search would not identify σ_s from the gradient alone. Repeated observations of the same workers separate these forces.

Search persistence. Repeated observations of search separate persistent differences in the willingness to move from transitory variation in search choices. To isolate this information, hold non-amenity worker and job characteristics fixed, abstract from endogenous survivor selection, and consider the amenity process in its stationary distribution F_q. Since search-choice shocks are independent across dates and independent of the amenity process, they do not contribute to the covariance of search across time. Match amenities, by contrast, preserve differences in search propensities until an independent redraw occurs. The probability of no redraw over k months is $(1-\zeta)^k$. Consequently, the autocorrelation of search at firm rank y equals this persistence factor

multiplied by the amenity-driven share of search variation:

$$\rho_k(y) = (1-\zeta)^k \omega_F(y) \qquad k \geqslant 1, \tag{29}$$

where $\omega_F(y)$ denotes the variance share evaluated under F_q. Thus, the decay across lags, $\rho_{k+1}(y)/\rho_k(y) = 1-\zeta$, reveals amenity persistence, while the level of the correlations, conditional on that persistence, reveals the importance of differences in match-specific search propensities. Together with the search gradient, persistence therefore disciplines both the dispersion of amenities σ_q and the scale of the search-choice shock σ_s: once $\omega(y)$ is known, so is the attenuation in equation (28). Conditional on these two quantities, the average level of search pins down the fixed cost κ.

Search in durable matches. Search in long-tenure matches is informative about the frequency of resets. In the data, search levels off at long tenures once age effects are removed. The decline in search with employer tenure reflects the net effect of two opposing forces. Selective retention lowers average search, because workers who search are more likely to leave. Amenity resets raise search, because a redrawn amenity is on average worse than that of a surviving match. At a limiting tenure distribution, the two forces must offset each other:

$$\zeta\,(p_F - p_\infty) = -(1-\zeta)\,\frac{\mathrm{Cov}_\infty(P, r)}{\bar{r}_\infty}, \tag{30}$$

where p_∞ is the search rate in long-tenure matches, p_F the search rate in a match with a freshly drawn amenity, r the probability that a match survives to the next month, and $\bar{r}_\infty$ and Cov_∞ the mean and covariance under the limiting tenure distribution. Because search and survival are negatively correlated, the right-hand side is positive. Conditional on search and selection parameters, the long-tenure search rate therefore disciplines the frequency of amenity resets.

Remaining parameters. Table 3 summarizes the external calibrations and target moments. Under the identifying assumption that unemployed workers accept all offers, hires from unemployment recover the education-specific distribution of observed offer characteristics, while search participation, job finding, and hiring channels discipline the unemployed offer-arrival technology. Appendix Figure A.15 summarizes education-specific differences in destination firm ranks following unemployment, and outside-sector destination shares, which are used to reconstruct education-specific offer distributions. I assess this assumption using model-implied acceptance rates. Contract and unemployment transitions discipline the contract and notice processes, while transitions between ranked employment, outside employment, and unemployment discipline outside-sector parameters. Appendix F develops these arguments. Internally estimated parameters are fitted jointly.

6 Model Results

6.1 Fit and Discussion of Parameters

Model fit. The model provides a very good fit to the main patterns of search behavior and labor mobility. Figure 6 compares the model with the data on search and mobility across firms, search by tenure, and the persistence and concentration of search. Table A.14 reports the 20 moments targeted in estimation. Average search is 6.04 percent in the model and 6.02 percent in the data, while search persistence is 2.58 versus 2.60 in log-odds units. The model also closely matches the overall decline in search across firm productivity ranks. It captures the substantial difference in employer-to-employer mobility between searchers and nonsearchers, and closely reproduces unemployment job finding and transitions across contract types. The main exception is the active share of inside-to-inside hires, which is 44.3 percent in the model compared with 55.8 percent in the data.

The model also captures the main patterns of search across the firm distribution, although it understates the steep decline at the lowest-ranked employers. Since systematic differences in job value across firms enter through pay premia, hours mismatch, and contract characteristics, this discrepancy suggests that additional non-pay disadvantages at low-ranked firms may further amplify inequality in job quality at the bottom of the distribution. Importantly, these employers account for a relatively small share of the workforce. The model closely reproduces the employment distribution across firm ranks, with the bottom fifth accounting for 7.5 percent of employment in the model and 6.2 percent in the data.

Beyond the targeted moments, the model performs well in reproducing the decline in employer-to-employer mobility across firm ranks. Although this profile is not targeted, the model captures it over much of the distribution, with the largest discrepancy again concentrated at the bottom. It also closely matches the shares of workers observed searching never, once, or repeatedly over eight quarterly interviews. Together, these untargeted patterns provide additional support for the model's account of selection into search and its implications for mobility.

Parameter Estimates. The deterministic component of the search cost is $\kappa = 1.535$, equivalent on average to 67.6 percent of monthly earnings among inside-sector employees. Since individuals generally engage in search conditional on receiving a favorable draw of the random search cost, the average realized cost is around 46.7 percent of monthly earnings.[23] The scale of the search cost shock is estimated at $\sigma_s = 0.231$. The standard deviation of the relative taste shock between searching and not searching equals approximately 27 percent of the fixed search cost, implying

[23] Kaas et al. (2026) estimate a model with binary search choices, a fixed utility cost of searching, and additive type-I extreme-value taste shocks. Their estimated shock scale is approximately 30 percent of the fixed search cost, compared with 15 percent in the model. The estimates in this paper therefore imply a sharper search response to changes in the gains from searching, measured relative to the fixed cost. Their CRRA consumption utility makes fixed costs in utility units not directly comparable to mine under linear utility. For a worker earning their mean pay, assuming consumption equals after-tax earnings, their estimated fixed cost is equivalent to a consumption loss of approximately 60.5 percent of gross quarterly earnings, comparable to an estimate of 67.6 percent of monthly earnings in this paper.

that search choices respond sharply to changes in gains around the indifference threshold. Search costs are associated with a substantial increase in access to job offers. For employed workers, active search raises the monthly offer-arrival probability from 2.27 percent to 13.05 percent, an increase of 10.78 percentage points.

The model estimates a standard deviation of match-specific amenities among job offers of $\sigma_q = 0.613$. This dispersion is economically substantial: holding hours and contract characteristics fixed, a one-standard-deviation improvement is equivalent, on average across inside-sector offers, to a 27.7 percent pay increase in current-period utility.[24] Amenities are also highly persistent. The monthly reset probability of 0.626 percent implies a mean waiting time of 13.3 years between redraws, absent match termination. Together, substantial amenity dispersion and persistence create scope for lasting gains from sorting, while costly search limits their realization.

6.2 External Benchmarks

Figure 7 compares the model with external evidence on offer arrivals, acceptance, and job valuations. Since mobility reflects both offer receipt and willingness to move, matching transition rates alone need not imply that either component is accurately captured. Using US survey data, Faberman et al. (2022) report that 2.6 percent of employed and 4.2 percent of unemployed workers receive an unsolicited offer over four weeks. The model's monthly passive offer probabilities are 2.27 percent and 3.47 percent, respectively. The model thus generates broadly comparable offer opportunities, including their greater prevalence among unemployed workers. Among employed offer recipients, Faberman et al. (2022) find that 48.8 percent of searchers and 10.6 percent of nonsearchers accept or intend to accept their best formal offer. The corresponding model acceptance rates are 55.2 percent and 16.7 percent. Although both rates are slightly higher than in the data, the model closely reproduces the gap: 38.5 versus 38.2 percentage points. This contrast supports the model's selection mechanism: workers more willing to accept outside opportunities are also more likely to search.[25]

To shed light on the distribution of outside options and non-pecuniary returns to mobility, I compare the model to recent experimental estimates. Caldwell et al. (2025) find that 39 percent of workers prefer their current job to an alternative paying 20 percent more. The model counterpart is 34.9 percent, comparing full continuation values with an alternative offering permanently higher pay and an independent amenity draw, holding other job characteristics fixed. Unlike the survey,

[24]The pay equivalent is σ_q/z, where z denotes the pay-dependent component of flow utility. For comparison, Table 2 in Hall and Mueller (2018) estimates a standard deviation of 0.34 in log-pay units for the independent component of non-wage job values, equivalent to a pay increase of $e^{0.34} - 1 \approx 40.5$ percent. The conversion applied here isolates residual match amenities and omits hours mismatch and contract security which may provide additional sources of non-wage heterogeneity in the model.

[25]To provide a European comparison, I use the Consumer Expectations Survey conducted by the ECB. Its January 2025 wave elicited the number of job offers received over the preceding three months and whether respondents had accepted any of them. Since Sweden was not covered by the survey, I focus on Finland, the only Nordic country in the sample. Among Finnish respondents employed in both adjacent interviews, I construct a quasi-acceptance rate by dividing the weighted number of workers accepting at least one offer by the weighted total number of offers received. I construct the same statistic in the model, requiring inside-sector employment at both endpoints of the three-month window. The resulting quasi-acceptance rate is 22.6 percent in the model, closely matching the 21.5 percent observed in the Finnish data.

this alternative is not drawn from worker-named employers. Finally, Humlum et al. (2026) find that voluntary job movers in Denmark require an average premium of 25.85 percent over current pay to return to their previous job. Among recent direct employer-to-employer movers, the model counterpart is 19.9 percent, calculated by equating continuation values and applying the same ± 100 percent cap to individual premia. This comparison assesses the gains in non-pay job value generated through sorting.

Overall, the model fits the external evidence remarkably well, suggesting that the extent of preference heterogeneity, the offer arrival process, and the elasticity of search with respect to acceptance rates are well captured by the model.

6.3 Endogenous Search and Labor Supply Elasticity

Search Elasticities and Endogenous Exposure to Outside Options. Cross-sectional pay gradients in search combine the effect of pay with sorting on match-specific amenities, hours preferences, and contract situations, and therefore need not recover how workers respond to a change in pay at a given employer. The estimated model separates the two. I vary an individual employer's pay while holding non-pay job characteristics and outside opportunities fixed, and evaluate workers' search decisions. The implied search elasticity is -10.07, 42.4 percent larger in magnitude than the model-implied cross-sectional elasticity of -7.07, evaluated at the same employment weights and mean search rate. The cross-sectional gradient therefore understates the response of search to pay.

How do changes in active search affect the exposure to outside options? The estimated model implies that at baseline, active search generates 22.3 percent of the offers received by inside-sector employees. Most offers are therefore unsolicited.[26] Since reduced search affects only the active component of offer arrival, a search elasticity of 10.07 translates into an offer-arrival elasticity of 2.24. A 1 percent increase in employer pay therefore reduces the average offer-arrival probability by approximately 2.2 percent. Understanding the production process of offers is therefore crucial to understand how search elasticity parameters shape the responsiveness of outside options.

Implications for Labor Supply Elasticities I next examine how these behavioral responses translate into changes in the employer's stationary workforce, allowing its composition to adjust over time. The employment effect of lower search depends on whether the forgone offers would have been accepted and how long the workers retained would remain at the firm. To isolate the contribution of search, I compare the estimated model with a benchmark that holds incumbent workers' state-specific search probabilities at their baseline values. Acceptance decisions and stationary workforce composition adjust in both cases. Higher pay can therefore retain workers by making competing offers less attractive in both regimes. Endogenous search adds a reduction in workers' exposure to outside offers.

[26]The relatively small active share of offers partly reflects the low prevalence of search. As a back-of-the-envelope comparison, holding the estimated offer-arrival parameters fixed, a search rate of 25 percent would imply that approximately 54 percent of offers were generated through active search, compared with 22.3 percent at the estimated search rate of 6 percent.

Figure 9 summarizes the employment response and its recruitment and retention components, while Table 4 reports the underlying elasticities. Allowing search to respond to pay raises the stationary employment elasticity from 3.66 to 4.98, an increase of 1.33 elasticity points, or 36.3 percent. This amplification operates almost entirely through retention. The recruitment elasticity remains approximately 1.66, while the contribution of retention rises from 2.00 to 3.33. Higher pay therefore increases employment substantially more when workers can adjust their search decisions.

The fixed-search benchmark already allows higher pay to reduce workers' willingness to accept outside offers. Endogenous search adds a reduction in the probability of actively seeking those offers. Consistent with this mechanism, the elasticity of the employer-to-employer quit rate changes from -3.12 to -5.40. These quits account for 52 percent of baseline separations. The aggregate employment-to-unemployment separation rate also becomes more responsive, with its elasticity changing from -1.33 to -1.83. State-specific layoff risks remain fixed, but their aggregate incidence changes as pay alters workforce composition and exposure to competing exits. Demographic exits are unresponsive by assumption. The channel-specific elasticities contribute to aggregate retention according to their baseline shares of separations.

The larger labor supply elasticity also implies less wage-setting power. Under the standard monopsony pricing condition, the inverse labor supply elasticity measures the gap between marginal revenue product and pay, expressed relative to pay.[27] Allowing search to respond lowers this implied markdown from 27 to 20 percent. The corresponding implied wage share rises from 78.5 to 83.3 percent of marginal revenue product. At a given marginal revenue product, this difference is equivalent to a wage about 6 percent higher. Ignoring the search margin would therefore overstate the inverse-elasticity measure of wage-setting power by about a third. I next examine how heterogeneity in workers' search responses, acceptance probabilities, and expected remaining tenure shapes the magnitude of this amplification.

The clearest implications concern employer-to-employer mobility. With search held fixed, recruitment from employment and quits to other employers respond almost symmetrically to pay, consistent with the symmetry in simple job-ladder models discussed in Card (2022). Among workers employed elsewhere who receive an offer from the firm, the elasticity of acceptance with respect to its pay is 3.24. Among incumbents, the elasticity of the employer-to-employer quit rate is -3.12 when search is held fixed. Allowing incumbents to adjust their search increases the magnitude of the quit elasticity to 5.40, while leaving the recruitment response unchanged. Endogenous search therefore introduces an asymmetry between recruitment and retention: higher pay attracts workers through greater offer acceptance, while retaining incumbents through both lower acceptance of competing offers and reduced exposure to those offers. The near-symmetry observed under fixed search consequently does not extend to the full mobility response. These results caution against

[27] Writing marginal revenue product as MRP, the condition implies $(\text{MRP} - w)/w = 1/\varepsilon^{N}_{w}$, or equivalently $w/\text{MRP} = \varepsilon^{N}_{w}/(1 + \varepsilon^{N}_{w})$. These calculations evaluate the pricing condition using the local labor supply elasticities. The reported elasticities measure headcount employment. Weighting workers by their education-specific ability yields elasticities of 3.68 with fixed search and 5.02 with endogenous search, leaving the amplification from search essentially unchanged.

using well-identified offer-acceptance responses alone to infer the overall labor supply elasticity. In the estimated model, holding search fixed yields an employment elasticity of 3.66, about a quarter below the elasticity of 4.98 when search adjusts, despite allowing acceptance decisions and workforce composition to respond in both cases. The additional employment response comes from how pay changes incumbents' exposure to competing offers, a margin that acceptance elasticities alone do not capture.

6.4 Heterogeneity in Search Propensities

The average elasticity of search is not sufficient to determine its contribution to firm labor supply. A reduction in search affects employment only insofar as it prevents an outside offer that would have been accepted. The contribution of search therefore depends on the joint distribution of search responsiveness, offer acceptance, and expected remaining match duration.

Figure 8a shows that search responses are concentrated among workers close to indifference between searching and not searching. This concentration is consistent with the binary search decision and the relatively small scale of search-cost shocks. Quantitatively, 20 percent of incumbents account for 83 percent of the decline in active search following a small increase in employer pay.

I next decompose the contribution of endogenous search to the firm's labor supply elasticity into three components: the average search response, selection through offer acceptance, and adjustment in workforce composition. In discrete time, the local decomposition is

$$\Delta\varepsilon_w^N = \theta^Q \frac{\bar{Q}}{\bar{S}} \left\{ \mathbb{E}_p[D] + \frac{\mathrm{Cov}_p(A, D)}{\mathbb{E}_p[A]} + \mathbb{E}_{pA}\left[D(x) \left\{ \bar{S}(1-\delta(x))(\Pi T)(x) - 1 \right\} \right] \right\}. \tag{31}$$

Here, $D(x) = -\partial \log p(x) / \partial \log w$ denotes the negative of the search elasticity, while $\mathbb{E}_p$ and $\mathbb{E}_{pA}$ weight the incumbent distribution by search propensities $p(x)$ and the product of search propensities and acceptance rates $p(x)A(x)$, respectively. The factor $\theta^Q \bar{Q}/\bar{S}$ is the share of separations generated through active search. Finally, $T(x)$ denotes expected remaining employer tenure, Π the within-match transition kernel, and $\delta(x)$ the conditional exogenous separation probability.

Figure 10 shows the three components. The average search response contributes 2.38 elasticity points, which would raise the firm's labor supply elasticity from 3.66 to 6.03. Accounting for the covariance between acceptance probabilities and search elasticities reduces this benchmark by 0.34 elasticity points, to 5.69. Figure 8b illustrates the heterogeneity underlying this adjustment. The search elasticity is hump-shaped across acceptance probabilities. Highly attached incumbents who reject all offers exhibit lower elasticities. At the other extreme, workers who have a very high acceptance rate of outside offers, for example due to a negative reset, adjust their search action only to a limited extent in response to an increase in the firm's pay policy. In the estimated distribution of active searchers, additionally weighting workers by their acceptance probabilities lowers the

magnitude of the average search elasticity from 10.07 to 8.63. The covariance term is therefore negative: the workers most willing to accept outside offers are, on average, less responsive at the search margin. Selection into search and selection in response to pay therefore operate differently. Active searchers are more willing to accept outside offers than nonsearchers, but workers whose search declines following a raise are less willing to accept offers than the average active searcher. The least attached workers remain strongly inclined to search even after a small pay increase.

The workforce adjustment reduces the contribution of search by a further 0.71 elasticity points, from 2.04 to 1.33, yielding an overall employment elasticity of 4.98. Figure 8c plots the average decline in search following a 1 percent pay increase as a function of expected remaining tenure among incumbent workers. Again, the decline is hump-shaped. The search decisions of workers with known contract expiration, or very high attachment, respond little to increases in the firm's pay policy. Changes in pay mainly affect marginal workers with unfavorable match-specific valuations of the firm. The additional matches preserved through lower search effort are disproportionately drawn from workers with relatively weak attachment to their employer. Although a reduction in their search prevents some immediate departures, these workers are less likely to remain employed at the firm for an extended period. Consequently, the employment gains from reduced search are smaller than a calculation based on the average separation rate would suggest. For the employment response, the relevant duration weights each worker by both their decline in search and their probability of accepting an offer. Under these weights, expected remaining tenure is approximately 43 months, compared with the aggregate completed-spell benchmark of 66 months. Workers retained through reduced search therefore generate fewer expected future months of employment than the benchmark would imply. This limits the contribution of reduced search to long-run employment.

Together, selection on offer acceptance and on expected match duration attenuate the amplification from endogenous search by 44 percent relative to the mean-response benchmark. The decomposition also clarifies what can be learned from a pay experiment that measures workers' search responses, of the kind discussed in Kline (2025). Consider a small, permanent increase in employer pay, holding outside opportunities and non-pay characteristics fixed, with search measured among baseline incumbents before workforce composition adjusts. As shown in Appendix C.5, the resulting elasticity of average search equals the search-weighted average of individual elasticities, which is -10.07 in the model's baseline workforce. Combining this response with the share of separations generated through active search, as in the homogeneous-worker formula of Proposition 1, predicts a contribution of 2.38 points to the employment elasticity. The heterogeneous model instead delivers 1.33 points, 44 percent less. The difference reflects which workers reduce search, whether their offers would have been accepted, and how long the preserved matches would last. Even a correctly measured average search response therefore does not, by itself, identify the contribution of search to firm labor supply.

7 Conclusion

This paper studies how workers' search decisions and heterogeneous preferences over jobs interact to shape labor mobility and labor supply to firms. Using a nationally representative survey linked to Swedish employer–employee records and firm balance sheets, I document four facts: (i) on-the-job search declines along the job ladder, with a substantially steeper gradient in firms' productivity ranks than in their pay ranks; (ii) search remains substantial at the highest-ranked employers, where idiosyncratic, non-pecuniary motives predominate; and (iii) search is highly concentrated and persistent over time; and (iv) search is highly concentrated and persistent across workers, yet rises within continuing matches as workers' desire to try something new grows. Together, these findings are consistent with workers exerting costly search effort to sort into jobs based on persistent but evolving preferences.

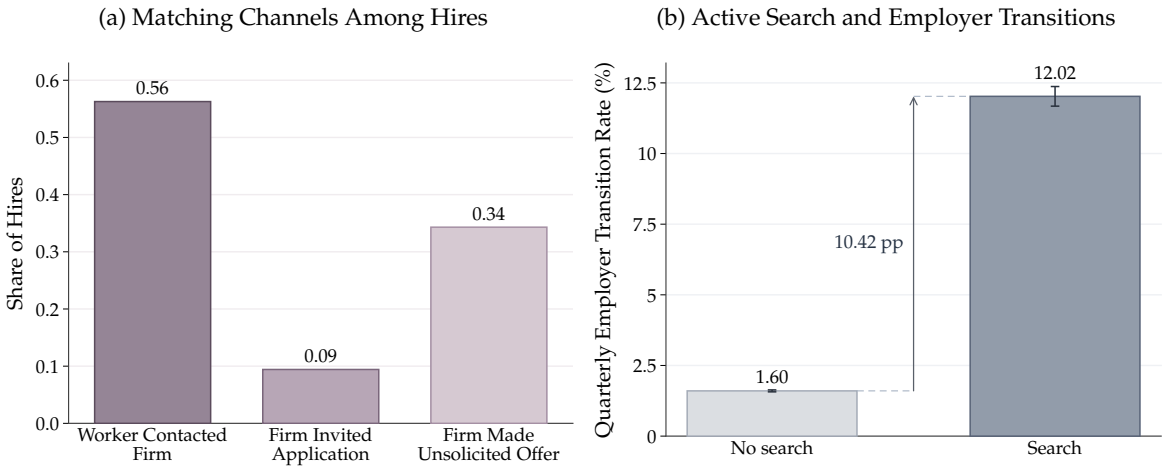
To interpret these patterns, I develop and estimate a dynamic random search model with a binary search decision, unsolicited offers, and evolving match-specific amenities. Jobs differ in pay, hours mismatch, and employment security, while workers differ in their valuations of particular worker–firm matches. The model gives attachment to the current employer a dual role: it determines both workers' willingness to accept competing offers and their incentive to seek those offers in the first place. Search and mobility allow workers to sort into valued matches, reducing the returns to further search, while changes in match-specific amenities can induce renewed search within otherwise durable employment relationships. The estimated model reproduces the dynamics of search and mobility and their distribution across firms, and its predictions regarding the offer arrival process, acceptance behavior, and workers' willingness to stay are consistent with external survey evidence.

The quantitative results establish endogenous search as an important component of labor supply to firms. Allowing search to respond to pay raises the stationary employment elasticity from 3.66 to 4.98, an increase of approximately 36 percent relative to a counterfactual that fixes state-specific search probabilities at their baseline values. Under the standard steady-state formula, endogenous search lowers the implied markdown from 27 to 20 percent of pay. Heterogeneity substantially moderates the amplification from endogenous search. In the model, 20 percent of incumbents account for 83 percent of the decline in search effort following marginal changes in pay. Workers most willing to accept outside offers are, on average, less responsive at the search margin, while the matches preserved through reduced search have relatively short remaining durations. Accounting for heterogeneity in attachment reduces the contribution of search by 44 percent relative to a benchmark based on the response of average search. Even a causal estimate of the average search response therefore does not generally identify its contribution to firm employment.

Understanding the microeconomic foundations of firm labor supply is a central frontier in the study of labor market competition (Kline, 2025). The findings in this paper show that endogenous search effort constitutes a crucial component of the labor supply elasticity faced by firms. The findings also qualify what experimental estimates of worker responses can deliver on their own: acceptance responses conditional on receiving an offer omit the search margin, while an average

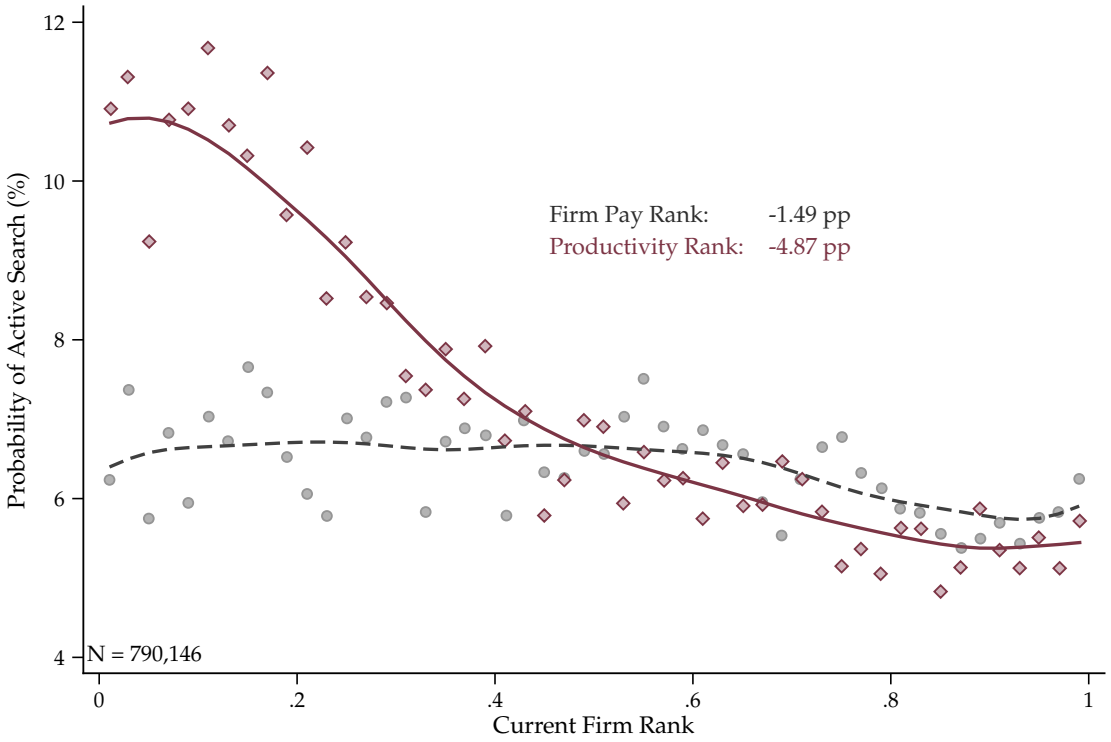
search response omits the heterogeneity that determines how reduced search translates into long-run retention. Assessing equilibrium implications of endogenous search and its role in the evaluation of labor market policies such as minimum wages is a promising avenue for future research.

Figure 1: Active Search and Labor Mobility



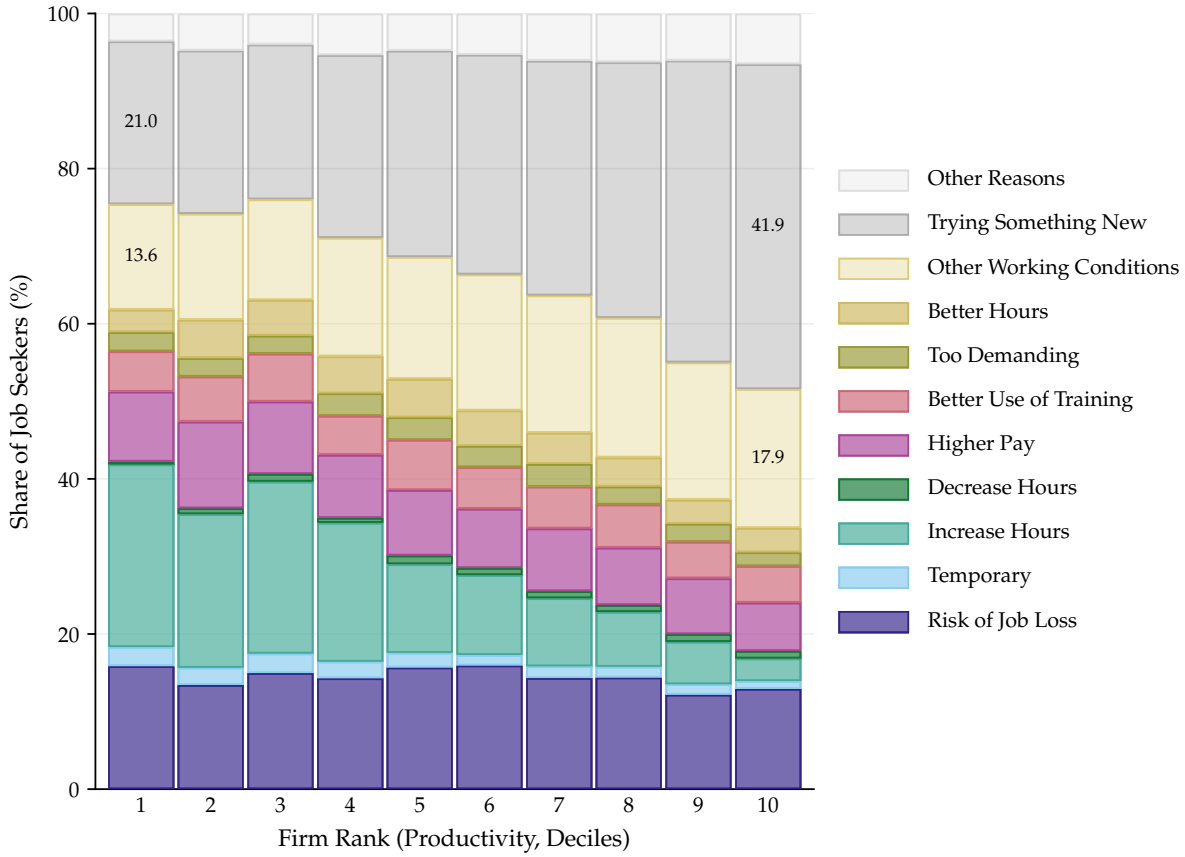
Notes: The figure documents the importance of active job search for employer-employer mobility. **Panel a)** shows the frequency of worker-initiated contacts versus firm-initiated, unsolicited contacts among workers recently hired from another employer. **Panel b)** shows the probability that a worker transitions to another employer over the next quarter by whether a worker engaged in active on-the-job search in the last four weeks.

Figure 2: Active Search Across Firms



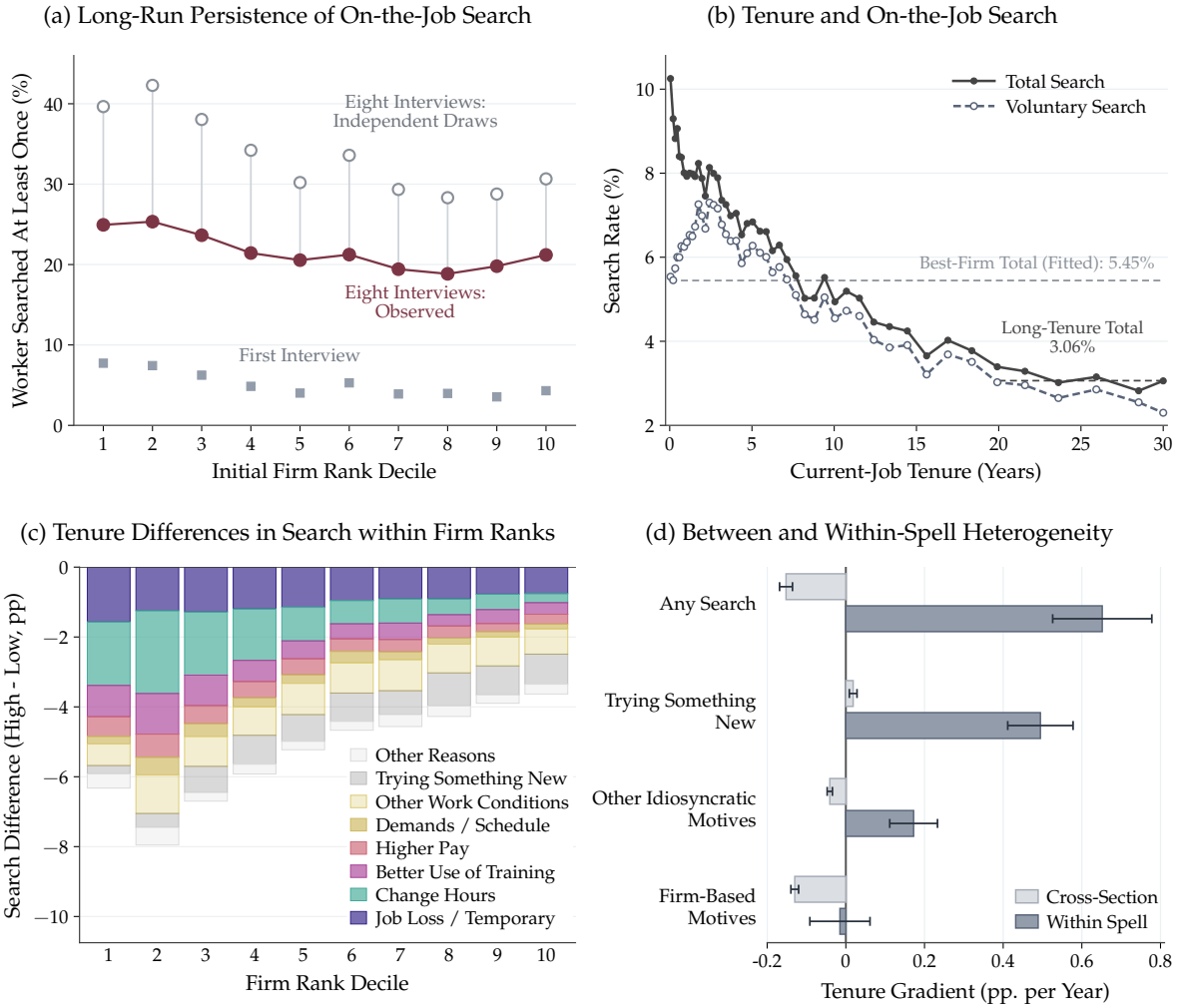
Notes: The figure presents a binned scatter plot of the relationship between the incidence of active job search and an employer's rank in the job ladder, induced by either firm pay premia (gray) or value added per worker (purple). For firm pay premia I plot the posterior estimates obtained from applying an Empirical Bayes Shrinkage assuming Normal parameter distributions.

Figure 3: Search Motives Across the Firm Ladder



Notes: The figure displays the distribution of primary motives for on-the-job search across the ranking of firms induced by value added per employee. The sample consists of employees who report having searched for another job in the past four weeks and state a reason for their job search.

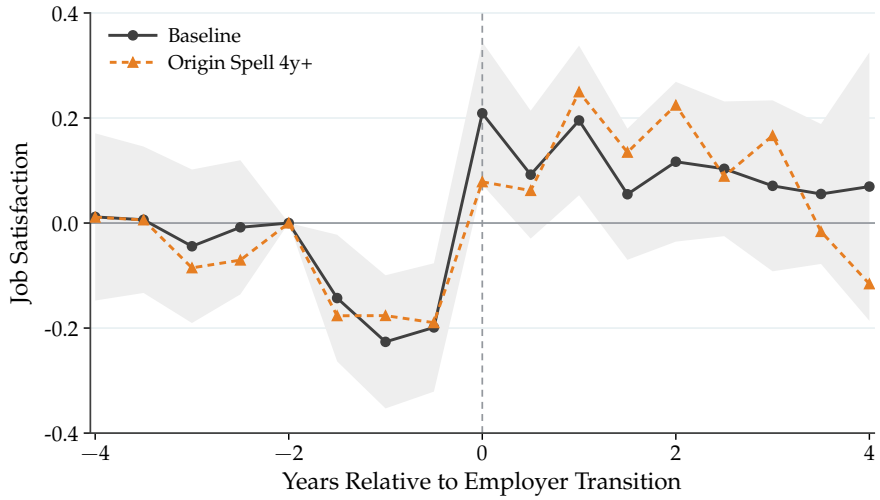
Figure 4: Search Persistence, Tenure, and Match Dynamics



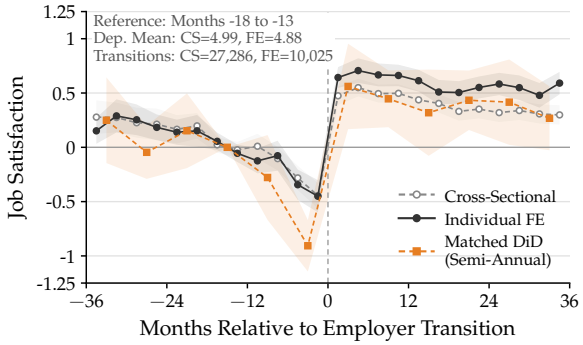
Notes: The figure illustrates heterogeneity in on-the-job search between and within employment spells. The sample consists of observations with valid self-reported tenure in the Swedish Labor Force Survey between 2005 and 2020. **Panel a)** plots the share of workers observed actively searching at least once, by the productivity decile of their employer at the first interview. Squares show search in the first interview; filled circles show search in at least one of eight quarterly interviews. Hollow circles show the predicted long-run share constructed from the observed search rate at each interview within each initial-employer decile, assuming independence across interviews. Search refers to active job search in the four weeks preceding each interview. **Panel b)** shows the age-corrected profile of on-the-job search in years of tenure spent with the current employer. The age adjustment utilizes the on-the-job search rate of recent hires from unemployment. Estimates also control for calendar-year fixed effects. Hollow markers present estimates for voluntary on-the-job search, excluding search due to anticipated risk of job loss or contract expiration. **Panel c)** shows the difference in search by motive between workers with more than 10 years of tenure versus workers with less than 10 years of tenure at their current employer across the distribution of firms. **Panel d)** shows parametric estimates of the relationship between tenure and search due to different motives in cross-section and panel models. Light gray bars depict the coefficient of a linear projection of search on employer tenure in years. Dark gray bars show coefficients when panel fixed effects are included in the model. I restrict the sample to workers who are observed at least 12 months before the eventual end of their current employer spell and exhibit at least four usable interviews within the spell. Standard errors are clustered at the individual level. Whiskers show 95 percent confidence intervals.

Figure 5: Dynamics of Job Satisfaction Around Employer Transitions

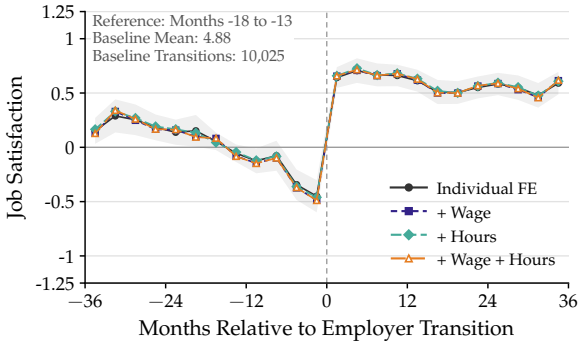
(a) Job Satisfaction (AMU)



(b) Alternative Estimators (UK-HLS)



(c) Controlling for Pecuniary Aspects (UK-HLS)

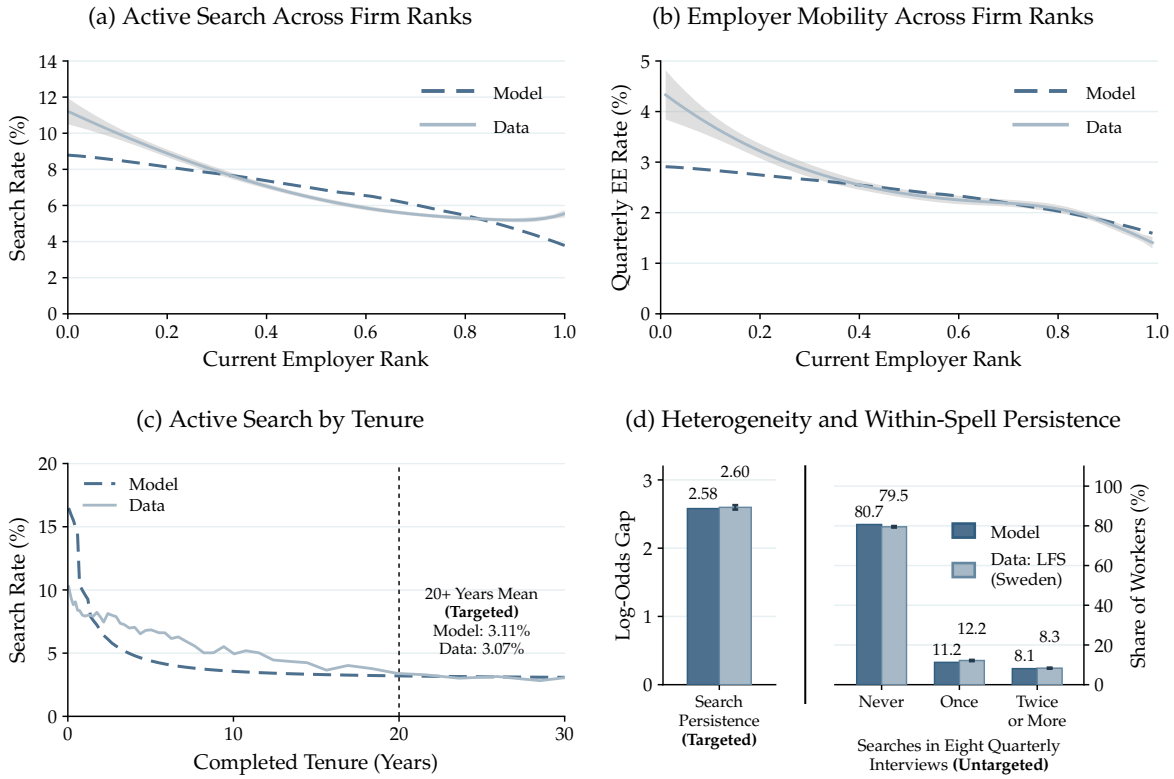


Notes: The figure shows the evolution of self-reported job satisfaction around employer transitions in Sweden and the United Kingdom. **Panel a)** presents a pseudo-event study of job satisfaction around employer transitions in the AMU. Dots represent the coefficient estimates of the regression

$$Y_i = \sum_{\substack{k \in \mathcal{K} \\ k \neq -4}} \alpha_k \mathbb{1}[t_i - t_{s(i)} \in T_k] + \mathbf{X}_i' \beta + \lambda_{t_i} + \epsilon_i, \tag{32}$$

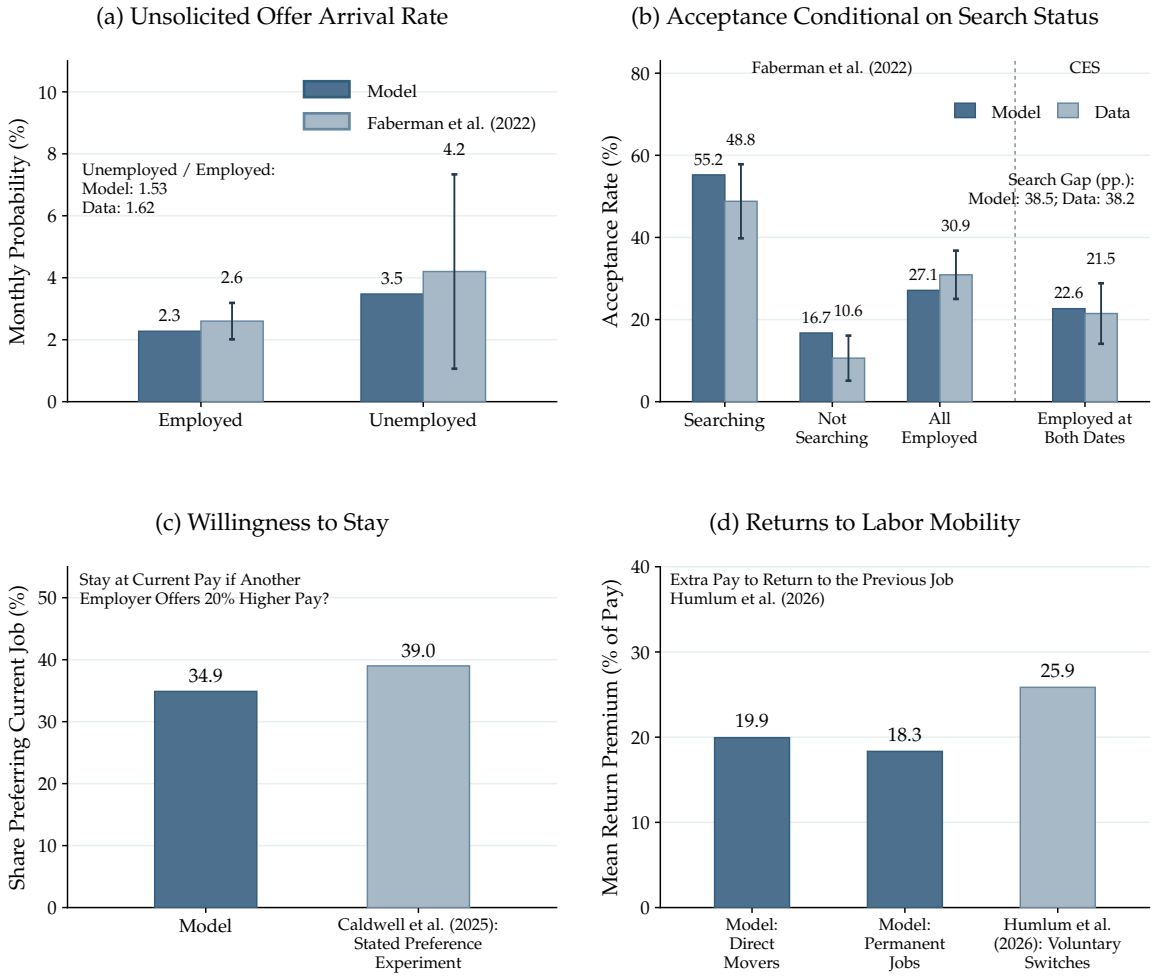
where Y_i denotes the job satisfaction of individual i, t_i is the calendar month at which individual i is interviewed, and $t_{s(i)}$ is the calendar month of the employer transition closest to the interview date. The vector $\mathbf{X}_i$ includes education-gender-specific cubic polynomials in age, while λ_{t_i} denotes calendar-year-by-month fixed effects. Event time is grouped into six-month intervals T_k, with months -24 through -19 as the omitted category. **Panel b)** compares cross-sectional, individual fixed-effects, and matched difference-in-differences estimates using the UK Household Longitudinal Study (UK-HLS). The cross-sectional and individual fixed-effects specifications include demographic-by-year and interview-month fixed effects; the latter additionally includes individual fixed effects. These profiles use three-month event-time bins. The matched difference-in-differences specification compares movers with workers never observed changing employers, matched on baseline calendar year, age group, tenure group, and job satisfaction during months 24 to 13 before the transition. It includes stratum-treated-status, stratum-event-quarter, and calendar-year fixed effects. Event-time coefficients are estimated in six-month bins using the underlying quarterly observations. **Panel c)** compares the individual fixed-effects specification with specifications additionally controlling for log gross monthly pay, log normal weekly hours, and both controls jointly. All UK-HLS profiles are expressed relative to months 18 to 13 before the employer transition. Shaded areas show 95 percent confidence intervals; Standard errors are clustered at the individual level.

Figure 6: Model Fit: Search and Mobility Across Firms and Tenure



Notes: The figure compares model-implied outcomes with their empirical counterparts. Dark blue denotes the model and light blue the data; model curves are dashed. **Panel (a)** shows search rates by current employer rank. The search–rank gradient enters the calibration, but individual points along the profile are not separately targeted. **Panel (b)** shows quarterly employer-to-employer transition probabilities by origin employer rank, measured as employment at a different employer three months later, conditional on initial employment and labor-force survival over the quarter. **Panel (c)** shows search rates by completed employer tenure. The shaded region identifies tenure of at least 20 years. The reported targeted mean is calculated for permanent-contract workers over the full 20+ tenure distribution, including tenures beyond the displayed range. The inset reports descriptive tenure gradients in percentage points per year: pooled regressions in the cross-sectional row and employer-spell fixed-effects regressions in the within-spell row. These estimates use restricted samples with at least four usable interviews per spell after excluding observations in the final year before an employer change or transition to unemployment; they are not slopes fitted to the displayed profile. **Panel (d)** distinguishes targeted search persistence from the untargeted distribution of repeated search. On the left-hand scale, persistence is the difference in the log odds of current search between prior-quarter searchers and nonsearchers, conditional on observing the same employer at consecutive quarterly interviews. On the right-hand scale, bars report the proportions observed searching zero, once, or at least twice across eight quarterly interviews, conditional on employment at all eight observation dates; employer changes are allowed. "Never" therefore means never observed searching, rather than no search between interviews. Untargeted statistics do not enter the calibration criterion directly. Bands around empirical curves and whiskers on empirical bars indicate sampling uncertainty; model parameter uncertainty is not displayed.

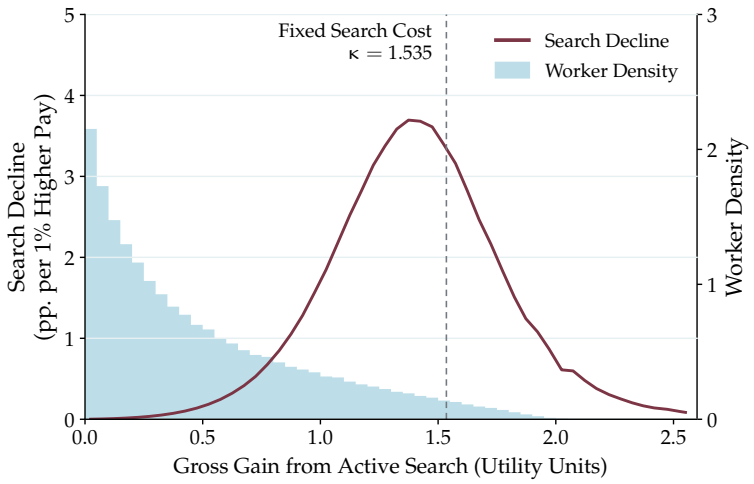
Figure 7: Offer Arrival Process, Acceptance Behavior and Selection



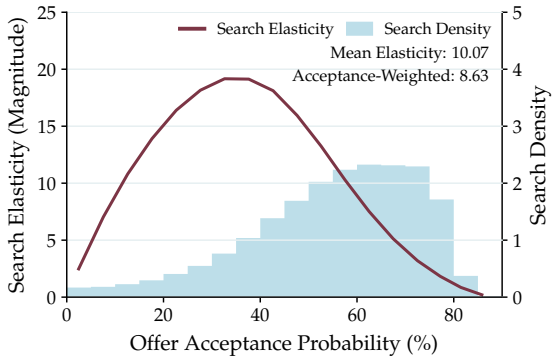
Notes: The figure compares moments of the offer process and acceptance behavior in the model to external benchmarks. **Panel a)** compares the monthly unsolicited offer arrival rate λ_0 in the model to the unsolicited offer arrival rate estimated in Faberman et al. (2022). Point estimates and standard errors are taken from Table IV, Panel B. Whiskers represent 95 percent confidence intervals based on the reported standard errors. **Panel b)** compares the acceptance rate by search status with empirical estimates in Faberman et al. (2022). Empirical estimates in Table IV, Panel B, measure acceptance of the best formal offer received during the preceding four weeks, excluding offers for additional jobs. **Panel c)** compares the share preferring their current job at current pay to a worker-named alternative offering 20 percent more in Caldwell et al. (2025). The model compares full continuation values with an alternative offering permanently higher pay and an independent amenity draw, holding other worker and job characteristics fixed. Unlike the survey, the model alternative is not worker-named. **Panel d)** compares the mean pay premium required to choose the previous job over the current job with the estimate for voluntary switches from Table 2 in Humlum et al. (2026). The empirical measure pools hypothetical return and stay framings. Model workers are currently employed inside the sector and moved directly between inside-sector employers within the preceding three years. The second model bar additionally requires permanent contracts outside advance notice, measured before departure from the previous job and at the current interview. Required pay equates full continuation values, preserving the previous job's characteristics at departure. Premia are expressed relative to current gross monthly pay and capped at $\pm 100\%$ before averaging.

Figure 8: Heterogeneity in Returns to Search and Behavioral Responses

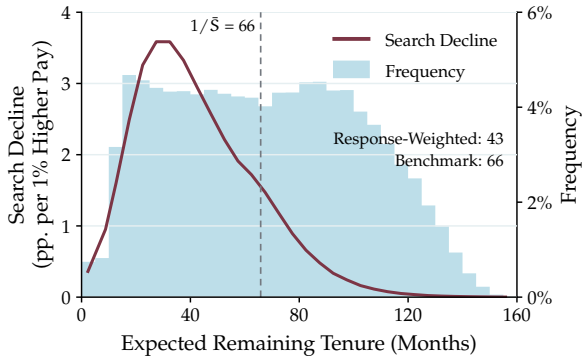
(a) Gains from Search and Search Responses to Pay Increase



(b) Elasticity of Search and Offer Acceptance

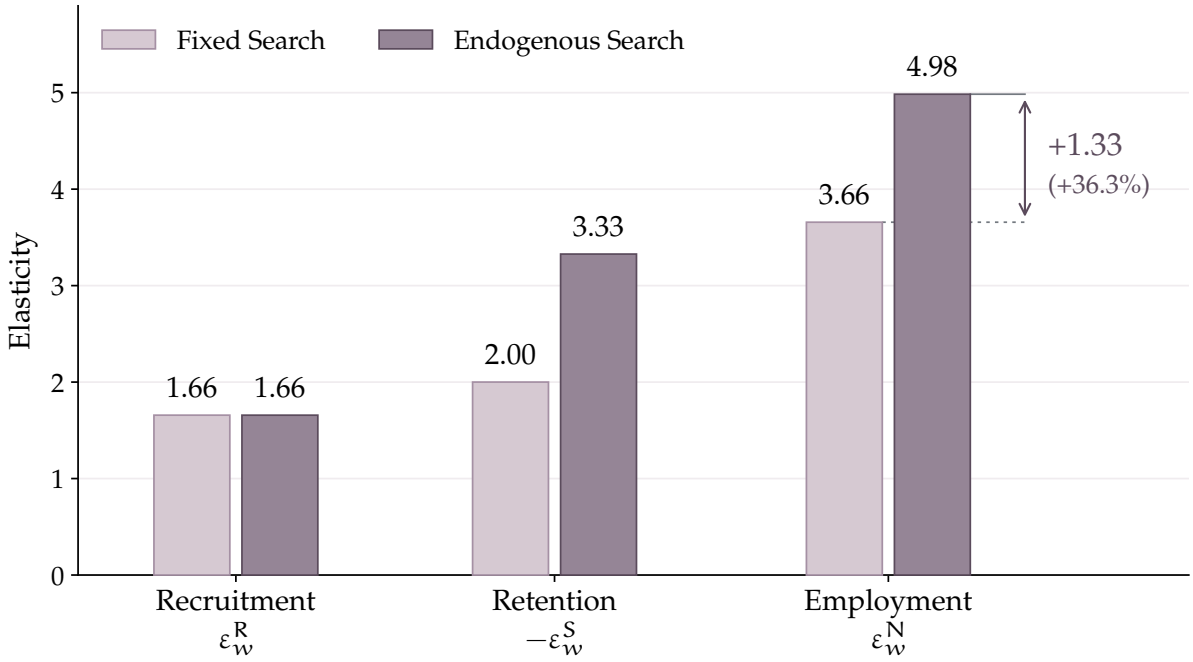


(c) Search Response by Expected Tenure



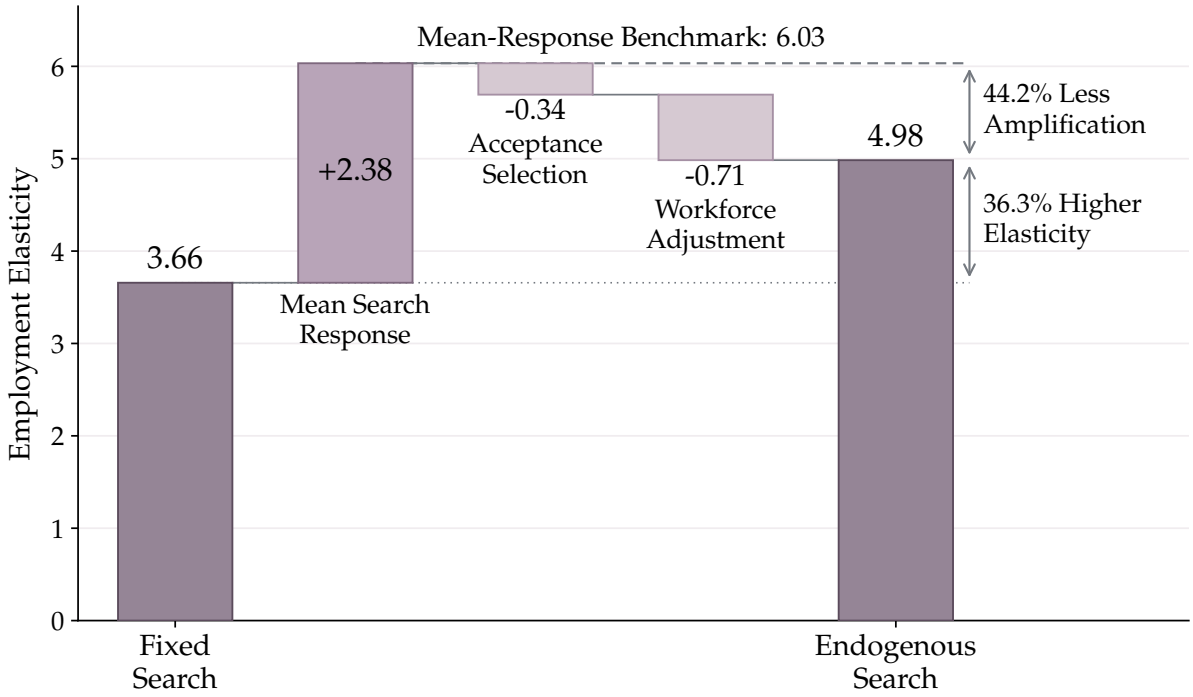
Notes: The figure illustrates heterogeneity in the elasticity of search with respect to a change in the firm's pay policy. **Panel a)** shows how the absolute declines in the propensity to search vary with the gross-gain of active search in the estimated model distribution. The gain from active search for an individual in state $\mathbf{x}$ prior to the realization of costs is given by $\tilde{\beta}\lambda_1\Omega(\mathbf{x})$ where $\Omega(\mathbf{x})$ is defined in equation (17). The dashed vertical line marks the deterministic cost component κ of active search. Blue bars depict the density of workers across gains from active search. The solid line represents the absolute decline in percentage points induced by a 1 percent increase in the firm's pay policy. **Panel b)** sheds light on the covariance of acceptance rates and heterogeneous search elasticities. Blue bars show the density of offer acceptance probabilities among active searchers. The red line represents the search elasticity with respect to the firm's pay policy conditional on the offer acceptance probability among active searchers. The figure reports the mean (unweighted) elasticity and the acceptance-weighted elasticity among active searchers. **Panel c)** shows the relationship between declines in search following a 1 percent increase in the firm's pay policy and expected tenure among incumbent workers. The x-axis marks the expected remaining tenure in months at the given firm. Blue bars show the distribution of workers across expected remaining tenure. The dashed vertical line marks the inverse average separation rate. The red line shows the decline of active search with respect to the firm's pay policy conditional on expected remaining tenure. Declines conditional on remaining tenure use the same search-acceptance weights as the density.

Figure 9: Endogenous Search and the Labor Supply Elasticity



Notes: The figure shows components of the labor supply elasticity across firms. Recruitment refers to the elasticity of hires from both employment and unemployment. Retention refers to the elasticity of separations from three sources: i) employer-employer quits, ii) separations into unemployment and iii) labor-force exit. The third set of bars presents the total labor supply elasticity given by $\epsilon_w^N = \epsilon_w^R - \epsilon_w^S$.

Figure 10: Heterogeneity Attenuates the Amplification from Search



Notes: The figure decomposes the contribution of endogenous search to the firm's stationary employment elasticity with respect to its own pay. *Fixed Search* holds baseline state-specific search probabilities fixed, whereas *Endogenous Search* allows these probabilities to adjust. Acceptance decisions and stationary workforce composition adjust in both cases. Outside opportunities and model parameters remain fixed. *Mean Search Response* represents the contribution of the search-weighted average search elasticity. *Acceptance Selection* captures the covariance between search responses and the probability of accepting an outside offer. *Workforce Adjustment* captures how changes in retention translate into stationary employment through remaining match durations and workforce composition. A negligible residual is omitted from the display but included in the endpoint and percentage calculations.

Table 1: Summary statistics

Variable	Analysis sample	Employed (%)
Female	34.9	49.1
Age	40.09	40.49
College Share	23.1	30.6
Permanent Contract	92.1	84.8
Underemployed	5.1	7.2
Searched in the last four weeks	6.4	7.2
Among Searchers		
Search for extra job	2.7	4.1
Search duration (weeks)	16.23	17.34
Number of Search Methods	2.13	2.18
Search Method	99.8	99.8
Contact Employers Directly	46.7	46.3
Contact Public Employment Agency	6.2	8.2
Contact Private Employment Agency	7.9	6.9
Contact Friends or Relatives	19.9	18.9
Consult Union	0.6	2.0
Place or Answer Ads	21.0	20.6
Read Openings in Newspapers/Internet	62.6	66.0
Other Means of Active Search	0.7	0.6
Primary reason for search		
Increase Hours	10.7	15.8
Decrease Hours	0.9	0.7
Risk of Job Loss	14.7	18.6
Temporary	1.8	2.9
Higher Pay	7.5	7.5
Better matches education	6.4	6.7
Too demanding	2.3	2.3
Better working hours	3.7	3.3
Other reasons related to working conditions	16.3	13.8
Trying something new	30.5	23.0
Other reason	5.1	5.2
Does not know	0.1	0.1
Prefer not to answer	0.1	0.0
Number of Observations	953,727	2,297,319

Notes: The table shows summary statistics for the analysis and the full population of employed respondents in the Labor Force Survey between 2005 and 2020. Underemployment is defined as respondents stating that they would like to work more than their current hours.

Table 2: Firm Characteristics and On-the-Job Search

	(1) Raw	(2) Baseline	(3) + Contract Type	(4) + Hours Mismatch	(5) + Occupation
Panel A. Firm Pay Premium					
Firm Pay Premium	-0.023	-0.026	-0.010	0.010	-0.002
	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)
Observations	748,319	747,632	747,632	746,668	576,807
R^2	0.000	0.023	0.035	0.054	0.031
Panel B. Firm Pay Rank					
Firm Pay Rank	-0.010	-0.011	-0.005	0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	748,319	747,632	747,632	746,668	576,807
R^2	0.000	0.023	0.035	0.054	0.031
Panel C. Value-Added Rank					
Value-Added Rank	-0.044	-0.047	-0.038	-0.025	-0.036
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Observations	792,533	791,768	791,768	790,716	614,655
R^2	0.002	0.025	0.036	0.055	0.032
Panel D. Specification					
Calendar-Month FE		✓	✓	✓	✓
Location × Year FE		✓	✓	✓	✓
Demographic FE		✓	✓	✓	✓
Family FE		✓	✓	✓	✓
Contract Type FE			✓	✓	
Hours Mismatch FE				✓	
Occupation FE					✓

Notes: The table presents regression results for the relationship between incidence of on-the-job search and a worker's position in the job ladder. Each cell reports the estimated slope of a linear projection of on-the-job search on a measure of the current employer's position in the job ladder. The outcome is a binary indicator that returns one if a worker actively engaged in on-the-job search in the last four weeks and zero otherwise. In **Panel a)** the independent variable is the current employer's firm pay premium as estimated in equation (10). In **Panel b)** the independent variable is the current employer's rank in the distribution of firm pay premia. In **Panel c)**, the independent variable is the employer's rank in the distribution of value-added per employee. The set of controls varies across columns. In Column (1), no controls are added to regression. Column (2) presents the estimates obtained when controlling for education-gender-age-year fixed effects, gender-specific indicator for the presence of a young child in the household, as well as calendar-month and municipality-year fixed effects. Column (3) additionally controls for the worker's contract type at the time of interview. Column (4) controls for the degree of hours mismatch. Specifically, I non-parametrically control for the number of hours a worker would like to work beyond what she can in her current job. Lastly, Column (5) presents alternative estimates adding occupation (4-digit level) fixed effects to the model in Column (2). Standard errors clustered at the individual level are reported in parentheses. The model is estimated at the worker level.

Table 3: Parameterization and Target Moments

Symbol	Parameter description	Value	Source/target
Panel A. Externally Calibrated and Fixed Parameters			
β	Monthly discount factor	0.9967	Annual interest rate of 4%
μ	Labor-force exit probability	0.003	Labor-force exit rate
b	Replacement rate	0.67	Average replacement rate
D_F	Fixed-term duration	8	Mean duration in vacancy postings
D_B	Probationary duration	6	Default statutory probationary period
D_N	Notice duration	6	Advance-notice duration
$a(e)$	Education-specific ability	By education	Mean earnings by education
$F(y, h, j \mid e)$	Joint offer distribution	Empirical	UE hires, by education
ϕ_e	Inside-sector offer share	By education	Inside UE share, prior I, by education
μ_q	Mean match amenity	0	Normalization
κ_h	Hours-deficit utility penalty	0.45	Fixed utility scaling
Panel B. Internally Estimated Parameters			
$(\lambda_0^u, \lambda_1^u)$	Offer arrival, unemployed	(0.035, 0.118)	UE rate; active-hire share
(λ_0, λ_1)	Offer arrival, employed	(0.023, 0.108)	EE rates by search; active-hire share
κ	Search cost	1.54	Mean on-the-job search
σ_s	Search-choice shock scale	0.23	Search rank slope; EE rates by search
ϕ_N	Notice-entry probability	0.00043	Permanent EU rates by search
δ_P	Direct permanent-job separation	0.00083	Permanent EU rates by search
ϕ_F^c	Fixed-term conversion	0.54	Same-firm fixed-term to permanent rate
(δ_B, δ_F)	Contract-expiry separation	(0.15, 0.42)	EU rates by temporary contract type
σ_q	Match-amenity dispersion	0.61	Search rank slope; search persistence
ζ	Amenity reset probability	0.0063	Search in permanent jobs, tenure 20+
$(o_e)_{e \in \mathcal{E}}$	Outside-sector flow payoffs	By education	Outside EE share from I, by education
σ_O	Outside choice-shock scale	13.45	Outside-destination log-odds contrast[a]
δ_o	Outside separation rate	0.45	Prior-O share of UE hires into I

Notes: See Appendix Table A.14 for details on the targeted moments, their data sources and the model fit.

Table 4: Labor Supply Elasticities and Implied Markdowns

	(1) Baseline Flow Share (%)	(2) Fixed Search	(3) Endogenous Search
Recruitment, ε_w^R	–	**1.66**	**1.66**
Acceptance: Unemployed, $\varepsilon_w^{A,U}$	56.3	0.43	0.43
Acceptance: Employed, $\varepsilon_w^{A,E}$	43.7	3.24	3.24
Retention, $-\varepsilon_w^S$	–	**2.00**	**3.33**
EE Quit Rate	52.0	−3.12	−5.40
EU Separation Rate	28.2	−1.33	−1.83
Demographic Exits	19.7	0.00	0.00
Stationary Employment, $\boldsymbol{\varepsilon_w^N}$	–	**3.66**	**4.98**
Implied Markdown, $1/\varepsilon_w^N$	–	0.27	0.20

Notes: Except for the final row, entries in Columns (2) and (3) are elasticities with respect to the focal employer's pay, holding outside opportunities and model parameters fixed. *Fixed Search* freezes baseline state-specific search probabilities within the focal job; acceptance and stationary workforce composition adjust in both regimes. Column (1) reports baseline shares of hires beneath recruitment and baseline shares of separations beneath retention; the baseline is common to both regimes. The indented entries are channel-specific elasticities, not additive contributions. Recruitment is the hire-share-weighted acceptance elasticity. Acceptance refers to offers from the focal employer; employed recipients pool inside- and outside-sector sources. Source populations, search choices, and offer exposures are fixed. Retention is the negative of the separation-share-weighted exit-rate elasticity, $-\varepsilon_w^S$, not the elasticity of the probability of staying. Separations include EE quits, EU transitions, and demographic exits; the demographic exit probability is fixed. Stationary employment satisfies $\varepsilon_w^N = \varepsilon_w^R - \varepsilon_w^S$. The implied markdown is $1/\varepsilon_w^N$. Endogenous Search raises the employment elasticity by 1.33 (36.3%). Elasticities use central log-pay differences with half-step 0.005. At half-step 0.01, unemployment acceptance is 0.457 (Fixed Search) and 0.455 (Endogenous Search); employed acceptance remains approximately 3.24. All calculations precede rounding. Finite differences and rounding can cause small discrepancies in the weighted identities and displayed totals.

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A Data

A.1 Identifying Employers in the LFS Reference Month

This appendix describes the procedure used to assign administrative employer identifiers to employed LFS respondents. The unit of observation is an employed person-reference-month observation in the LFS. The assignment is made using RAMS worker–employer records, administrative spell dates, annual earnings, and LFS information on the month and year in which the respondent started working for her current employer.

Table A.1 reports the number of observations assigned by each rule. The rules are applied sequentially, so that each observation is assigned by the first applicable rule in the hierarchy.

1. **Unique active plant in the reference month.** I first assign the plant if exactly one administrative plant is active in the LFS reference/interview month.

2. **Unique active plant matching the LFS start month.** If multiple plants are active in the reference month, I assign a plant only if exactly one active plant has an administrative start month matching the LFS-reported start month of the current job.

3. **Unique active plant matching one-digit industry.** If ambiguity remains, I assign the unique active plant whose one-digit administrative industry matches the one-digit industry reported in the LFS.

4. **Unique active firm.** If several plants are active but all belong to the same firm, I assign that firm and select the active plant with the highest annual earnings as the representative plant.

5. **Reference-year/start-year overlap.** For observations not resolved by active-month information, I compare the set of plants observed in the LFS reference year with the set observed in the LFS-reported current-job start year. If their intersection contains exactly one plant, I assign that plant.

6. **LFS workplace-token continuity.** I use the LFS workplace number only as a within-LFS continuity token, not as a direct administrative establishment identifier. Within person–start-year– workplace-token cells, I fill unmatched observations from stronger source matches only when the candidate plant is also observed in the target administrative year and the intersection is unique.

7. **Annual fallback rules.** I then assign a plant when the worker has a single annual plant in the reference year; when a single substantive plant remains after excluding minor spells; or when the LFS-reported start year contains a single administrative plant and the reported start date is not after the reference month.

8. **Dominant annual earnings plant.** If multiple annual plants remain, I assign the highest-earnings plant only if it accounts for more than 75 percent of the worker's positive annual earnings across candidate plants.

9. **Previous-year fallback for long-tenure jobs.** For workers with at least 18 months of tenure in the current LFS job, I use the highest-earnings plant in the previous calendar year as an additional fallback.

10. **Within-spell fill and consistency correction.** Finally, I fill remaining gaps within stable current-job start-year cells when a unique or unique-modal source plant is available. I also correct isolated inconsistencies within stable LFS workplace-token spells when the previous and following LFS rows identify the same administrative plant.

Observations for which no administrative employer can be identified after all rules are assigned a no-match code and are excluded from specifications requiring firm-level characteristics.

The employer-linking procedure starts from 2,297,319 employed LFS person-reference-month observations. I assign an administrative employer identifier to 2,228,118 observations, or 97.0 percent of the sample. The highest-quality rules, which require the assigned administrative employment spell to be active in the LFS reference/interview month, account for 1,799,148 assignments (78.3 percent). Most of these are plant-precise active-month matches: 1,799,144 observations are assigned either because a single plant is active in the reference month, because a unique active plant matches the LFS-reported start month of the current job, or because a unique active plant matches the one-digit LFS industry. For observations not resolved by active-month information, I use set-overlap and workplace-token rules, which account for 198,261 assignments, followed by annual fallback rules, which account for 208,959 assignments. Finally, within-spell fill rules assign 20,874 observations, and a consistency correction within stable LFS workplace-token spells affects 876 observations. The remaining 69,201 observations, corresponding to 3.0 percent of the employed LFS sample, are left unmatched.

A.2 Search Motives in the LFS

Among other questions, the Swedish Labor Force Survey (*Arbetskraftsundersökningarna*) asks respondents: *Vilken är den främsta anledning till att du söker annat arbete (eller extraarbete)?*. This translates to: *What is the primary/main reason that you are seeking other work (or additional/extra work).* Respondents can then choose an answer from the following list:

1. Vill öka arbetstiden
   → *Wants to increase working hours*

2. Vill minska arbetstiden
   → *Wants to decrease working hours*

3. Risk att förlora nuvaranda arbete/nuvarande arbete tidsbegränsat
   → *At risk of losing current job/ current job is fixed-term*

4. Nuvarande arbete är ett arbete som up betraktar som tillfälligt, medan up söker annat arbete
   → *Regards the current job as temporary while looking for another job*

5. Nuvarande arbete är för fysiskt eller psykiskt krävande
   → *Current job is too physically or psychologically demanding*

6. Önskar högre lön
   → *Wants higher pay*

7. Önskar bättre arbetstider
   → *Wants better working hours*

8. Vill prova något nytt
   → *Wants to try something new*

9. Vill ha arbete som bättre motsvarar utbildningen
   → *Wants a job that better matches the individual's education*

10. Andra skäl som har med arbetsförhållandena att göra (t.ex. arbetets innehall, resor)
    → *Other reasons related to working conditions (e.g. job content, commuting)*

88 Vet ej
   → *Don't know*

98 Övrigt
   → *Other*

11. Vill ej svara
    → *Prefer not to answer*

A.3 Vacancy Postings

I use the universe of job advertisements published between 2006 and 2025 on *Platsbanken*, a nationwide vacancy board operated by the Swedish Public Employment Service (*Arbetsförmedlingen*) and Sweden's largest job-search website. Employers can post advertisements free of charge. The unit of observation is a job advertisement, which may cover more than one intended hire. Each posting contains standardized information on the occupation, employer, workplace location, publication and application dates, and employment conditions, including contract type, working time, duration, and remuneration type. I supplement these fields with information extracted from the advertisement text, which describes job tasks, required qualifications and skills, and non-wage job attributes. The remuneration field records how pay is determined rather than the wage level, and exact wages are rarely stated in either the structured fields or the free-text description.

Platsbanken has broad aggregate coverage of the Swedish vacancy market (Hensvik et al., 2021), but it does not capture all hiring opportunities, and the advertisements posted on the platform are not necessarily representative of all vacancies. Employers also recruit through their own websites, private job boards, recruitment agencies, referrals, and informal networks, so the composition of postings on Platsbanken need not be representative of the vacancy market as a

whole. In particular, central-government authorities are generally required to notify the Public Employment Service when recruiting externally, whereas no corresponding general requirement applies to private employers, municipalities, or regions. Central-government vacancies may therefore be disproportionately represented, while vacancies filled through other recruitment channels are omitted. To reduce compositional confounding, I control for employer sector in the main specifications. These controls do not, however, eliminate selection into Platsbanken.

Linking Vacancy Postings to Balance-Sheets To characterize firms analogously to the main analysis, we link job advertisements to firm-level balance-sheet data from Serrano. The Serrano data contain organization numbers that serve as unique firm identifiers, as well as firm names. The vacancy data contain employer names throughout the sample period and direct firm identifiers for a subset of postings. Direct identifiers are substantively available from 2018 onward: in 2018-2020 through organization numbers embedded in the external posting identifier, and from 2021 onward primarily through the employer organization-number field.

We proceed in four steps. First, we construct the population of firms in the Serrano balance-sheet data using the same firm-sample restrictions as in Section 3.3. We then link postings only to firms in this sample. Second, whenever the vacancy record contains a direct firm identifier, either the employer organization number or an organization number recovered from the external posting identifier, we match directly on that identifier. This step links 1.36 million postings, or 13.3 percent of the 10.26 million postings scanned between 2006 and 2024. Third, for postings without a direct identifier, we use an internal vacancy-name crosswalk. Specifically, when a normalized employer name is observed with a unique organization number in a given year, we assign that organization number to other postings in the same year with the same employer-name/workplace-name combination but missing direct identifiers. This step links an additional 0.72 million postings, or 7.0 percent of all postings. Finally, for remaining unmatched postings, we use the employer-name information in the vacancy data to match postings to firm names in the Serrano balance-sheet data. I first apply a standard normalization to both vacancy employer names and Serrano firm names by lower-casing, removing punctuation and legal suffixes, and standardizing common spelling variants. For each posting, I then construct candidate matches from the Serrano set of firms within year using exact normalized-name matches and fuzzy matches with high similarity. Cases that are exact and unique are accepted directly. For the remaining cases, I leverage GPT to adjudicate and select a candidate. Name-based matching links an additional 0.74 million postings, or 7.2 percent of all postings scanned between 2006 and 2024.

Overall, the linkage assigns 2.82 million postings, or 27.5 percent of all postings, to firms in the Serrano sample. Of these matched postings, 48.3 percent are linked using direct identifiers, 25.6 percent using the internal vacancy-name crosswalk, and 26.1 percent using Serrano firm-name matches. Requiring a same-year Serrano firm rank leaves 2.30 million postings. Excluding conservative staffing-firm links yields the final nonstaffing ranked sample of 2.27 million postings, corresponding to 4.08 million advertised vacancies.

A.4 External Survey

Consumer Expectations Survey To disentangle offer arrival from acceptance, I rely on the Consumer Expectations Survey (CES). The CES is an online survey conducted monthly by the ECB since 2020 that asks a variety of questions about households' expectations, economic conditions, and labor-market outcomes. The survey targets adults aged 18 and above in participating euro-area countries. For this analysis, I use the job-offer questions contained in the quarterly labor-market module fielded in January 2025 (wave 61). First, individuals were asked whether they had received any job offers in the previous three months. Conditional on reporting at least one offer, they were then asked: "How many job offers have you received in the last 3 months?" Respondents were instructed to consider all offers, including job offers from their current employer for a different position. Finally, respondents were asked whether they had accepted any job offer in the previous three months.

The sample contains approximately 3,000 respondents in France, Germany, Italy, and Spain, and approximately 1,000 respondents in Austria, Belgium, Finland, Greece, Ireland, the Netherlands, and Portugal. I restrict attention to employed respondents with valid responses to the offer-receipt question. For the benchmark Finnish moment, this leaves 678 employed respondents, of whom 122 report at least one offer. I construct an offer-level acceptance proxy as the weighted number of respondents accepting at least one offer divided by the weighted reported number of offers. The offer-count question is top-coded at "more than three"; I code this category as four, so the denominator is conservative. Because the acceptance question records whether any offer was accepted, rather than the number of accepted offers, the resulting measure should be interpreted as an approximate offer-level acceptance rate.

Appendix Table A.12 reports these moments for Finland and the pooled sample of participating countries. The Finnish offer-level acceptance proxy is 23.44 percent, with a standard error of 2.91 percentage points, compared with 11.77 percent and 0.56 percentage points in the pooled sample.

B Additional Empirical Results

B.1 Job Satisfaction Dynamics

I pool all waves of the UK-HLS between 2009 and 2024. Like the Swedish Work Environment Survey, the survey asks respondents to rate their job satisfaction on a seven-point Likert scale ranging from "completely dissatisfied" (1) to "completely satisfied" (7). I use this to proxy for the valuation of the ongoing match. Compared to the Swedish Work Environment Survey, the UK-HLS has two advantages. First, it is large and contains 316,913 valid job satisfaction reports prior to sample selection. Second, it is longitudinal as 69.6 percent of interviewees are observed again in the following year. As a result, the UK-HLS provides 242,084 cases from 44,376 individuals in which job satisfaction is observed in adjacent years, allowing me to conduct a richer analysis of job satisfaction dynamics.

In order to identify employer transitions I use a survey question that asks whether the respondent's current employer is the same as at the previous interview. A worker is coded as having changed employer when they report that their current employer is different from the employer reported in the previous survey wave. Because interviews are typically annual, this measure captures whether at least one employer transition occurred between two interviews; it does not rule out the possibility that a respondent changed employer more than once between interviews. To measure tenure, I use the reported date at which the respondent started working in their current job. This is not identical to employer tenure in all cases, since a job may change within the same employer, for example following a promotion or internal transfer. To reduce measurement error, I construct employer spell tenure using the earliest current-job start date observed within an employer spell. This assigns the spell the earliest observed start date among observations that are linked to the same employer spell.

Let v_{it} denote job satisfaction of worker i at time t. Let G_i denote the month of worker i's first observed employer transition. For a worker with a valid event-time measure, define

$$r_{it} = t - G_i \tag{B.1}$$

I then group event-time into quarterly bins

$$R_{it}^k = \mathbb{1}\{r_{it} \in B_k\}, \qquad k \in \{-K, \dots, K\}. \tag{B.2}$$

where B_k denotes the set of months in event quarter k. In the quarterly specification, $K = 12$, so the event window spans four years before and after the transition. I set the sixth quarter prior to the transition to be the omitted category. Workers without an observed employer transition are retained as stayers. Their role depends on the specification, as described below. Because UK-HLS tenure is measured for the respondent's current job, I cannot impose an analogous origin-employer tenure requirement after the worker has moved. The restriction is therefore asymmetric: it applies to observations before the transition, but not to post-transition observations. In the matched-DiD design, the same logic is implemented at the baseline observation: treated movers and eligible stayers must have at least 36 months of tenure at the baseline job before matching.

Cross-sectional pattern As a first step, I replicate the cross-sectional analysis in the Swedish Work Environment Survey presented in the main text. This specification provides the closest analogue to the Swedish survey evidence, but in a larger sample and at a higher frequency. I estimate

$$v_{it} = \sum_{k \neq k_0} \mu_k R_{it}^k + \mathbf{X}_{it}\beta + \eta_t + \epsilon_{it} \tag{B.3}$$

where $\mathbf{X}_{it}$ is a set of gender-education-age-year dummies, η_t is a calendar-month fixed-effect, and ϵ_{it} is an idiosyncratic error in reported job satisfaction. The omitted quarter dummy refers to the sixth quarter prior to transition, hence each coefficient μ_k should be understood as the

difference in job satisfaction in quarter k relative to the baseline quarter k_0. Standard errors are clustered at the individual level. While I restrict pre-transition observations to workers with tenure of at least three years to partially control for selection, this still leaves room for selection based on permanent worker or match quality. Matches observed close to separation may differ from matches observed far from separation even after conditioning on observables. The cross-sectional event study therefore provides a useful descriptive benchmark, but it does not by itself identify within-worker deterioration in match value.

Within-worker event profile To address permanent differences in workers' reporting behavior and average match quality, I exploit the longitudinal dimension of the UK-HLS and estimate the following within-worker event-study specification:

$$\nu_{it} = \sum_{k \neq k_0} \mu_k R_{it}^k + \mathbf{X}_{it}\beta + \phi_i + \eta_t + \epsilon_{it} \tag{B.4}$$

where ϕ_i is an individual fixed effect. The inclusion of individual fixed effects absorbs permanent differences in workers' reporting behavior and average match quality. The coefficients are therefore identified from within-worker changes in job satisfaction around employer transitions.

Matched Design As an alternative, I estimate a matched stayer event-study. I first identify individuals who are observed reporting their job satisfaction between five and eight quarters prior to an observed employer transition and have at least 36 months of tenure at their current employer. The reason for pooling across one year is that a relatively small number of individuals are observed exactly six quarters prior to a transition. If individuals have several observations within this window, I choose the observation closest to the eighteenth month prior to the transition. I refer to these individuals selected in this way as movers. For each mover, I select a control observation that is observationally similar to the mover in the base period, that is, six quarters prior to the move. I require that control observations have been with their employer for more than three years in the base period and remain with the employer for three more years following the base period.[28] From the set of eligible candidates, I chose controls that resemble the mover in terms of age, tenure and baseline job satisfaction. Specifically, I discretize age into five-year bins and tenure into four duration categories.[29] Matching is with replacement. The final sample consists of 1,016 unique treated individuals and 889 unique control persons.

Let $\widetilde{G}_{ip}$ denote the actual transition month for mover i and the placebo transition month for the matched stayer in matched pair p. I define placebo event time as

$$\widetilde{r}_{ipt} = t - \widetilde{G}_{ip},$$

[28] This restriction ensures that the dynamics within a two-year window around the employer transition are identified off comparisons with individuals who do not exhibit the pre-move decline in job satisfaction suggested by other specifications.

[29] In cases where multiple candidates satisfy the same interaction as the mover, I use a weighted average of the distance to the mover to adjudicate.

and construct event-time indicators $\widetilde{R}^k_{ipt}$ analogously to R^k_{it}. I estimate

$$y_{ipt} = \alpha_{ip} + \eta_t + \sum_{k \neq k_0} \gamma_k \widetilde{R}^k_{ipt} + \sum_{k \neq k_0} \theta_k \left(D_i \times \widetilde{R}^k_{ipt} \right) + u_{ipt}, \tag{B.5}$$

where D_i indicates movers, α_{ip} denotes a unit fixed effect in the stacked matched sample, and η_t denotes calendar-month fixed effects. Standard errors are clustered at the original individual level.

This design differs from the fixed effects regressions in (B.4) in the way it uses observations that do not exhibit employer transitions. By matching on baseline job satisfaction and comparing movers to stayers observed at the same calendar time, it controls for changes in satisfaction that are common across stable employment spells.

Results Figure A.5 presents the results. The cross-sectional profile in Panel a) exhibits a modest decline up to one year before the transition, followed by a sharp pre-transition drop and a subsequent, persistent increase relative to the baseline. As shown in Panel b), this pattern persists when controlling for individual fixed effects. Moreover, the matched stayer estimator reproduces the same pattern albeit with wider confidence intervals.

Panels c) and d) probe into the mechanisms of the pre-transition decline in job satisfaction. In Panel c), I estimate the panel model in (B.4) controlling for (log) hourly wages and hours. These controls do not change the estimated profile of job satisfaction, suggesting that time-varying shocks to wages or underemployment cannot account for the pre-transition decline. In Panel d), I restrict the sample to observations that likely reflect voluntary, unconstrained transitions. Specifically, I leverage the fact that the UK-HLS asks workers retrospectively about the reason for separating from their last employer and classify transitions as voluntary if separations did not occur due to contract expiration, or redundancy. Alternatively, I restrict the sample to transitions where respondents reported "leaving for a better job". Neither restriction has a significant impact on the overall profile of job satisfaction. This finding suggests that declines in job satisfaction pre-transition reflect a form of motivated reasoning that "protects" workers from the consequences of an inevitable separation.

B.2 Vacancies

Hiring Delays We measure the transition periods between offer and job starting date as the difference between stated starting date and the application deadline, assuming that employers collect all applications before sending out offers. The assumption of an instantaneous link between active search and offers is common in the literature (Faberman et al., 2022; Zuchuat et al., 2023; Cortés et al., 2023). For example, Marinescu and Skandalis (2021) show that the hazard from unemployment is mostly driven by applications in the preceding month.

In order to extract the exact starting dates from text, we rely on simple, rules-based methods. For example, we remove words such as "from" or "preliminary". Furthermore, we set mentions of "in the middle of month" to the 15th of a given month, and assign mentions of "fall term" to the 15th of August, and "winter term" to the 15th of January in line with Swedish conventions. The

median transition period is less than a month, and only around 9.2 percent of all vacancies feature transition periods longer than three months. For comparison, Davis and de la Parra (2024) estimate that the time between the end of posting (corresponding to our application deadline) and the start of employment amounts to 47 days for the US.

A limitation of the data is that firms who have interest in hiring as soon as possible might select into including starting date information, leading us to potentially underestimate the hiring lag. To address this concern, we rely on information from survey questions about the job start expectations of the unemployed in the LFS. Specifically, the LFS asks unemployed respondents who are not searching for work whether they already have a job lined up, and whether the starting date lies more than three months ahead. Among the unemployed with known starting dates, the share of those starting in more than three months is around 7.2 percent. Given that this figure is close to the corresponding moment estimated from the posting data, we view this as evidence that transition periods among employer to employer transitions are generally short.

Amenities I construct measures of workplace amenities from the text of vacancy postings. I start from the taxonomy of advertised job attributes in Audoly et al. (2024) and adapt it to the Swedish vacancy-posting context. Their dictionary contains around 47 attribute categories. As a first step, I use this taxonomy to define a set of broad candidate categories and then detect Swedish-language terms that relate to these categories. Specifically, I draw a random sample of 10,000 postings with non-empty description text from the vacancy corpus between 2006 and 2025 and instruct a large language model to extract short exact text snippets that explicitly mention an offered job attribute or disamenity. The prompt instructs the model not to infer amenities from occupation, employer identity, or context, and not to treat worker requirements or generic recruitment language as amenities.

In a second step, I aggregate the extracted snippets into candidate dictionary entries and compress them into a deterministic dictionary. This step is also assisted by a large language model, but only for dictionary construction: the model groups recurring Swedish snippets into conservative phrase families that can be implemented as regular expressions. I then filter the proposed phrase families to remove ambiguous or weakly identified expressions. As a rule, candidate phrases must be observed at least twice in the discovery sample, with limited exceptions for rare but concrete benefits. The final full-corpus measurement is therefore not produced by the language model directly, but by applying a fixed regular-expression dictionary to all vacancy postings.

Relative to Audoly et al. (2024), I make three main changes. First, I treat contract type, working hours, and wage-setting language as separate objects of analysis rather than components of the amenity index. Second, I exclude incentive-pay and collective-agreement language from the amenity index. Incentive pay is conceptually closer to compensation than to non-pay amenities, while collective-agreement coverage is difficult to interpret as an amenity per se conditional on other job characteristics. Third, I treat broad workplace and task-content categories conservatively. For example, I exclude central-location language because many phrases capture city names, office

locations, or public-sector workplace descriptions rather than a clearly valued workplace amenity. I similarly exclude generic statements about good colleagues, team culture, inclusion, career ladders, or interesting tasks unless they can be tied to a concrete and mechanically identifiable job attribute.

The resulting dictionary contains roughly two dozen category-level indicators, which can be divided into the following broad groups: i) material benefits, such as provision of a company vehicle, supplemental insurance, meal perks, parking, private pensions, and wellness benefits; ii) working arrangements, such as remote work, flexible hours, evening and night work, weekend and holiday work, shift work, and on-call work; iii) task-related amenities, namely autonomy and responsibility, and mission and sustainability; and iv) employer-provided training, namely on-boarding and mentoring programs, as well as general training.

To summarize the extent of amenity provision in a single scalar, I construct an amenity index by counting the number of amenities and disamenities mentioned in a posting. Let $\mathcal{J}$ denote the set of job attributes, partitioned into amenities and disamenities. Let ϕ_j denote the sign of job attribute j, which assumes the value of 1 if job attribute j is an amenity, and -1 if it is a disamenity. Let m_j be the number of times an attribute j is mentioned in posting i. We construct the amenity index as follows

$$a_i = \sum_{j \in \mathcal{J}} \phi_j \mathbb{1}[m_{ij} > 0]. \tag{B.6}$$

Figure A.8 shows the relationship between amenities and a firm's rank in the productivity distribution. I restrict the analysis to firms with at least five postings. Panel a) shows that the probability that a firm mentions an amenity in any of its postings is not uniform across the distribution. Higher ranked firms are more likely to mention amenities, though the increase is modest for most of the support – going from the 10th to the 90th percentile of the firm distribution increases the probability that a firm has mentioned an amenity in its postings from 70 to 75 percent. Panel b) shows that the amenity index mirrors this pattern exhibiting a small increase with the firm rank. The firm rank gradient is negligible compared to the between-firm dispersion that persists at any point in the distribution. A linear regression of firm-level amenity averages on the firm rank explains less than 1 percent of the variance in the dependent variable. This suggests that most variation in amenities does not amplify the value of jobs across the uniform ranking of firms maintained in the rest of the paper. Panel c) shows that this conclusion largely holds true when restricting the sample to firms with any mention of amenities. Panel d) shows the relationship between individual amenity categories and firm rank. For each category, the outcome is the firm-level share of postings that mention that amenity or disamenity component. The figure plots the slope from a linear regression of this firm-level incidence rate on firm rank, normalized by the category's mean incidence. The individual coefficients reveal that working-time arrangements, especially evening and night work as well as weekend and holiday work, differ most strongly across the firm distribution. Moving from the bottom to the top of the firm-rank distribution is associated with a decline in evening/night work and weekend/holiday work of about two times their mean firm-level incidence.

C Stylized Model and Proofs

C.1 Labor Supply Elasticity Under Random Search

Recall that the quit rate satisfies

$$Q(w, q) = \lambda(s(w, q))\mathcal{A}(w, q) \tag{C.1}$$

Taking the derivative with respect to the wage w yields

$$\frac{\partial Q(w, q)}{\partial w} = \frac{\partial \lambda(s(w, q))}{\partial s(w, q)} \frac{\partial s(w, q)}{\partial w} \mathcal{A}(w, q) + \lambda(s(w, q)) \frac{\partial \mathcal{A}(w, q)}{\partial w} \tag{C.2}$$

The quit response has two components stemming from two distinct behavioral margin: changes in the offer arrival rate, and changes in the acceptance rate

$$\epsilon^{Q}_{w}(w, q) = \epsilon^{\lambda}_{s}(w, q)\epsilon^{s}_{w}(w, q) + \epsilon^{\mathcal{A}}_{w}(w, q) \tag{C.3}$$

Under random search, recruitment is given by

$$R(w, q) = \int \lambda(s(w', q'))\mathcal{P}(w', q', w, q) dG(w', q') \tag{C.4}$$

Since the employer is atomistic, her pay decision does not alter the behavior of workers at competing employers. The recruitment elasticity is a weighted average of the acceptance elasticity, with high-search individuals receiving higher weights.

$$\frac{\partial R(w, q)}{\partial w} = \int \lambda(s(w', q')) \frac{\partial \mathcal{P}(w', q', w, q)}{\partial w} dG(w', q') \tag{C.5}$$

The recruitment elasticity is given by the search-acceptance weighted average of individual acceptance elasticities

$$\epsilon^{R}_{w} = \int \frac{\lambda(s(w', q'))\mathcal{P}(w', q', w, q)}{R(w, q)} \epsilon^{\mathcal{P}}_{w}(w', q') dG(w', q') \tag{C.6}$$

For $R(w, q) > 0$, define the recruitment weights

$$\omega(w', q', w, q) = \frac{\lambda(s(w', q'))\mathcal{P}(w', q', w, q)}{R(w, q)}. \tag{C.7}$$

Then the labor supply elasticity conditional on match amenity q is given by

$$\epsilon^{N}_{w} = \mathbb{E}_{\omega}[\epsilon^{\mathcal{P}}_{w}] - \frac{Q(w, q)}{\delta + Q(w, q)} \left[\epsilon^{\lambda}_{s}(w, q)\epsilon^{s}_{w}(w, q) + \epsilon^{\mathcal{A}}_{w}(w, q)\right] \tag{C.8}$$

Hence, labor supply depends on five components: (i) the acceptance elasticity among new hires, (ii) the share of voluntary quits among all separations, (iii) the offer arrival elasticity with respect to search effort, (iv) the search elasticity with respect to the firm pay premium and (v), the acceptance elasticity among incumbents.

Semi-Elasticities Since $\mathcal{A}$, $\mathcal{P}$ and s depend on (w, q) only through $V(w, q)$, the chain rule gives, for any such object X,

$$\epsilon_w^X = \frac{w}{X}\frac{\partial X}{\partial w} = wV_w \frac{d\log X}{dV}. \tag{C.9}$$

With $\mathcal{P}(w', q', w, q) = \Lambda\big((V(w, q) - V(w', q'))/\sigma\big)$ and $\Lambda'(z) = \Lambda(z)[1 - \Lambda(z)]$,

$$\epsilon_w^{\mathcal{P}}(w', q', w, q) = \frac{wV_w}{\sigma}\big[1 - \mathcal{P}(w', q', w, q)\big]. \tag{C.10}$$

Because V_w is evaluated at the recruiting firm's (w, q), it does not vary with (w', q') and factors out of the integral:

$$\mathbb{E}_\omega\big[\epsilon_w^{\mathcal{P}}\big] = \frac{wV_w}{\sigma}\,\bar{\mu}^R, \qquad \bar{\mu}^R \equiv \int \omega(w', q', w, q)\big[1 - \mathcal{P}(w', q', w, q)\big]\, dG(w', q'). \tag{C.11}$$

Turning to acceptance, with $\pi(V') = \Lambda\big((V' - V)/\sigma\big)$ and $\mathcal{A}(V) = \int \pi(V')\, dF(V')$,

$$\epsilon_w^{\mathcal{A}} = -\frac{wV_w}{\sigma}\,\bar{\mu}^Q, \qquad \bar{\mu}^Q \equiv \frac{\int \pi(V')\big[1 - \pi(V')\big]\, dF(V')}{\int \pi(V')\, dF(V')}. \tag{C.12}$$

Effort solves $\lambda'(s)\,\Omega(V) = c'(s)$, so s depends on V only through Ω. Using $\Omega'(V) = -\mathcal{A}(V)$,

$$\epsilon_w^s = \epsilon_\Omega^s\,\epsilon_w^\Omega = -\,\epsilon_\Omega^s\, wV_w\,\frac{\mathcal{A}}{\Omega}, \qquad \epsilon_\Omega^s = \frac{\lambda'(s)\,\Omega}{s\left[c''(s) - \lambda''(s)\,\Omega\right]}. \tag{C.13}$$

Substituting into the expression for ϵ_w^N,

$$\epsilon_w^N = \frac{wV_w}{\sigma}\,\bar{\mu}^R - \frac{Q}{\delta + Q}\left[-\,\epsilon_s^\lambda\,\epsilon_\Omega^s\, wV_w\,\frac{\mathcal{A}}{\Omega} - \frac{wV_w}{\sigma}\,\bar{\mu}^Q\right] \tag{C.14}$$

$$= wV_w\left\{\frac{\bar{\mu}^R}{\sigma} + \frac{Q}{\delta + Q}\left[\frac{\bar{\mu}^Q}{\sigma} + \epsilon_s^\lambda\,\epsilon_\Omega^s\,\frac{\mathcal{A}}{\Omega}\right]\right\}. \tag{C.15}$$

Since $\epsilon_w^N = wV_w\, d\log N/dV$, the term in braces is $d\log N/dV$. Taking the derivative with respect to w, and invoking the envelope theorem, implies that

$$V_w = \frac{1}{\rho + \delta + Q(w, q)} \tag{C.16}$$

This is due to the fact that the involuntary separation rate δ is independent of the wage.

$$\epsilon_w^N = \frac{w}{\rho+\delta+Q}\left[\frac{\bar{\mu}^R}{\sigma} + \frac{Q}{\delta+Q}\left(\frac{\bar{\mu}^Q}{\sigma} + \epsilon_s^\lambda\,\epsilon_\Omega^s\,\frac{\mathcal{A}}{\Omega}\right)\right] \tag{C.17}$$

Contribution of Behavioral Search Response Under Permanent Heterogeneity I now examine how the effect of a permanent wage change on long-run labor supply depends on the behavioral response of search. Consider an atomistic employer initially offering wage w_0, who changes the wage. Outside options and the search technology are held fixed. Importantly, I assume that amenities are permanent over the spell, that is, $\zeta = 0$. Throughout, search and elasticities will be functions of the permanent amenity q. I omit this dependence for the sake of exposition. Define the baseline value of employment $V_0 = V(w_0, q)$ and acceptance rate $\mathcal{A}_0 = \mathcal{A}(w_0, q)$. At baseline wage w_0, assume that baseline search is given by $s_0 = s(w_0, q)$, and is interior and differentiable. Then,

$$\lambda'(s_0) > 0 \qquad C_0 = c''(s_0) - \lambda''(s_0)\Omega(V_0) > 0. \tag{C.18}$$

Compare objects under endogenous search, denoted by E, against objects under the counterfactual holding search constant at this baseline level, denoted by C. Stationary employment satisfies

$$n^j(w, q) = \frac{R^j(w, q)}{\delta + Q^j(w, q)} \qquad j \in \{E, C\} \tag{C.19}$$

$$\varepsilon_w^{n,E} - \varepsilon_w^{n,C} = \frac{w_0[\lambda'(s_0)]^2 A_0^2}{(\delta+Q_0)(\rho+\delta+Q_0)C_0} > 0 \tag{C.20}$$

$$(\rho+\delta)V^j = w + q + \delta U - c(s^j) + \lambda(s^j)\Omega(V^j) \tag{C.21}$$

$$(\rho+\delta+Q_0)V_w^j = 1 + \underbrace{[\lambda'(s^j)\Omega(V^j) - c'(s^j)]}_{=0}\, s_w^j \tag{C.22}$$

It follows that

$$V_w^j = \frac{1}{\rho+\delta+Q_0} \tag{C.23}$$

for all $j \in \{E, C\}$. Given that values change equally regardless of the search response, the difference in quit hazards comes entirely from search effort

$$Q_w^E - Q_w^C = \lambda'(s_0)\mathcal{A}_0 s_w^E \tag{C.24}$$

Hence, the difference in labor supply elasticities is

$$\epsilon_w^{n,E} - \epsilon_w^{n,C} = -\frac{w_0\lambda'(s_0)\mathcal{A}_0}{\delta+Q_0} s_w^E \tag{C.25}$$

$$\varepsilon_w^{n,E} - \varepsilon_w^{n,C} = \frac{Q_0}{\delta+Q_0}\,\varepsilon_s^\lambda\left(-\varepsilon_w^{s,E}\right) \tag{C.26}$$

Finally, differentiating the optimal-search condition $c'(s) = \lambda'(s)\Omega(V)$, using $\Omega'(V) = -A(V)$, gives

$$C_0 s_w^E = -\lambda'(s_0)A_0 V_w = -\frac{\lambda'(s_0)A_0}{\rho + \delta + Q_0}. \tag{C.27}$$

Firm's problem. A firm with productivity p posts a wage w. Match amenities q are drawn from H when a job is offered, are observed before acceptance, and are not chosen by the firm. In steady state, employment in matches with amenity q and total employment are

$$n(w, q) = \frac{R(w, q)}{\delta + Q(w, q)}, \qquad N(w) = \int n(w, q)\, dH(q), \tag{C.28}$$

and the firm solves

$$\max_w (p - w)\, N(w). \tag{C.29}$$

The first-order condition gives the markdown

$$w = \frac{\bar{\epsilon}_w^N}{1 + \bar{\epsilon}_w^N}\, p, \qquad \bar{\epsilon}_w^N = \int \frac{n(w, q)}{N(w)}\, \epsilon_w^N(w, q)\, dH(q), \tag{C.30}$$

where $\epsilon_w^N(w, q)$ is the match-level elasticity derived above.

C.2 Stationary Employment with Evolving Match Amenities

Let Q denote the set of match amenities with its Borel σ-algebra, $B_b(Q)$ the bounded measurable functions on Q with the supremum norm, and $M(Q)$ the finite signed measures on Q. For $\mu \in M(Q)$ and $f \in B_b(Q)$ write $\mu f = \int f\, d\mu$. The operators below have kernels, $\mathcal{A}f(q) = \int \mathcal{A}(q, dq')f(q')$, and act on measures from the left via $(\mu\mathcal{A})(S) = \int \mu(dq)\, \mathcal{A}(q, S)$, so that $(\mu\mathcal{A})f = \mu(\mathcal{A}f)$.

$$\mathcal{L}f(q) = \lim_{h \to 0} \frac{\mathbb{E}[f(q_h) \mid q_0 = q] - f(q)}{h} \tag{C.31}$$

$$\mathbb{E}[f(q_h) \mid q_0 = q] = (1 - \zeta h)f(q) + \zeta h \int f(q')dF^q(q') + o(h) \tag{C.32}$$

$$\mathcal{L}f(q) = \zeta \left[\int f(q')\, dF^q(q') - f(q) \right] \tag{C.33}$$

Now, define the killed generator at the prevailing wage w

$$\mathcal{K}_w f(q) = \mathcal{L}f(q) - [\delta + \lambda(s(w, q))\mathcal{A}(w, q)]f(q) \tag{C.34}$$

Let r_w denote the measure of new employer matches by initial amenity and n_w the stationary measure of incumbent workers.

Let $r_w \in M_+(Q)$ denote the flow of new matches per unit time by initial amenity, and $n_w \in M_+(Q)$ the stationary stock of incumbents by current amenity, so that $N(w) = n_w \mathbf{1}$ and

$g = n_w/N(w)$. The stationary flow identity is

$$r_w + n_w \mathcal{K}_w = 0 \tag{C.35}$$

Now write $\mathcal{B}_w = -\mathcal{K}_w$ and assume that expected remaining tenure is uniformly finite over amenity states. Applying $\mathcal{B}_w^{-1}$ to $\mathbf{1}$ gives the expected amount of time a worker with match quality q will spend at the employer with wage w before a quit or an exogenous separation. Hence, expected remaining tenure is given by

$$T_w(q) = \left(\mathcal{B}_w^{-1}\mathbf{1}\right)(q) \tag{C.36}$$

Likewise, the stationary measure of incumbent workers is given by

$$n_w = r_w \mathcal{B}_w^{-1} \tag{C.37}$$

The total long-run employment prevailing at wage w equals the flow of hires in each initial state times the state-specific expected tenure, summed over states:

$$N(w) = n_w \mathbf{1} = r_w T_w \tag{C.38}$$

Applying $\mathcal{B}_w$ to the tenure equation yields

$$\mathcal{B}_w T_w = \mathbf{1} \tag{C.39}$$

By definition of $\mathcal{B}_w$, it follows that

$$1 = [\delta + Q(w, q) + \zeta] T_w(q) - \zeta \mathbb{E}_{q'}[T_w(q')] \tag{C.40}$$

where the expectation is taken over $q' \sim F^q$.

By the same envelope theorem argument as in the permanent-amenity case, the local derivatives of the value of employment under the endogenous and frozen search regimes satisfy

$$(\rho I + \mathcal{B}_0) V_w^j = \mathbf{1}, \qquad j \in \{E, C\}, \tag{C.41}$$

where $\mathcal{B}_0 = \mathcal{B}_{w_0}$ and all derivatives are evaluated at the common baseline wage w_0. Consequently,

$$V_w^E = V_w^C = (\rho I + \mathcal{B}_0)^{-1}\mathbf{1}.$$

Offer acceptance and recruitment therefore have identical local wage responses under the two regimes. The difference in stationary employment elasticities arises solely from the adjustment of incumbents' search effort.

To establish this result, let a dot denote differentiation with respect to log pay, evaluated at the common baseline wage w_0. Write n_0, N_0, and $g = n_0/N_0$ for the baseline employment measure,

total employment, and normalized incumbent distribution, respectively. Let $T = B_0^{-1}\mathbf{1}$ denote expected remaining match duration. In what follows, write $s(q) = s(w_0, q)$, $A(q) = \mathcal{A}(w_0, q)$, and $T(q) = T_{w_0}(q)$. Differentiating the stationary employment identity $n^j = r^j(B^j)^{-1}$ gives

$$\dot{N}^j = \dot{r}^j T - n_0 \dot{B}^j T, \qquad j \in \{E, C\}. \tag{C.42}$$

By the envelope theorem, $\dot{r}^E = \dot{r}^C$ at the common baseline. Moreover, the derivatives of offer acceptance coincide across regimes. Since the offer arrival rate is $\lambda(s) = \lambda_0 + \lambda_1 s$, the difference between the derivatives of the killed operators is therefore

$$[(\dot{B}^E - \dot{B}^C)f](q) = \lambda_1 A(q)\dot{s}(q)f(q), \tag{C.43}$$

where $\dot{s}(q)$ is the response of search effort to log pay under the endogenous-search regime. Under the counterfactual, search remains fixed at its baseline policy.

Subtracting the employment derivatives and normalizing by baseline employment yields

$$\Delta\varepsilon^N = -\lambda_1 \mathbb{E}_g \left[A(q)\dot{s}(q)T(q)\right].$$

Define the magnitude of the state-specific search elasticity by

$$D(q) = -\frac{\dot{s}(q)}{s(q)} = -\left.\frac{\partial \ln s(w, q)}{\partial \ln w}\right|_{w=w_0}.$$

It follows that

$$\Delta\varepsilon^N = \lambda_1 \mathbb{E}_g \left[s(q)A(q)D(q)T(q)\right]. \tag{C.44}$$

The expression has a direct interpretation. A reduction in search lowers the arrival rate of competing offers. The number of quits prevented depends on the probability that these offers would have been accepted, while the employment preserved by each prevented quit depends on expected remaining match duration. Consequently, the contribution of endogenous search depends on the joint distribution of search responsiveness, offer acceptance, and match duration among incumbent workers. Define

$$\mathbb{E}_s[D] = \frac{\int s(w, q)D(w, q)g(dq)}{\int s(w, q)g(dq)} \qquad \mathbb{E}_{sA}[D] = \frac{\int s(w, q)A(w, q)D(w, q)g(dq)}{\int s(w, q)A(w, q)g(dq)} \tag{C.45}$$

Using the share of quits attributable to search-generated offers, the contribution of endogenous search can be written as

$$\Delta\epsilon^N = \theta^Q \bar{Q} \mathbb{E}_{sA}\left[D(w, q)T(w, q)\right] \tag{C.46}$$

Dividing both sides by $\bar{S}$ and rearranging yields

$$\Delta\epsilon^N = \theta^Q \frac{\bar{Q}}{\bar{S}} \left\{\mathbb{E}_{sA}\left[D\right] + \mathbb{E}_{sA}\left[D(\bar{S}T - 1)\right]\right\} \tag{C.47}$$

The search-acceptance-weighted response differs from the average search response by a covariance term:

$$\mathbb{E}_{sA}[D] = \mathbb{E}_s[D] + \frac{\mathrm{Cov}_s(A, D)}{\mathbb{E}_s[A]}. \tag{C.48}$$

Substituting this identity yields the decomposition in Proposition 1.

C.3 Special Cases

Homogeneous incumbents. When incumbents are homogeneous, search, acceptance, and the quit hazard are common across workers, and expected remaining duration is $T = 1/(\delta + Q)$. The acceptance covariance and duration adjustment therefore vanish. The contribution of endogenous search simplifies to

$$\Delta\varepsilon_w^N = \frac{Q}{\delta + Q}\frac{\lambda_1 s}{\lambda(s)}D, \qquad D = -\varepsilon_w^s. \tag{C.49}$$

This recovers the earlier result: the absolute wage elasticity of search is weighted by the share of separations caused by accepted outside offers and the share of offers generated by active search.

Permanent amenities without exogenous separations. Suppose that $\zeta = \delta = 0$, with $Q(q) > 0$ for all relevant match types and finite stationary employment. Conditional on the permanent amenity q, the quit hazard remains constant throughout the employment relationship, so expected remaining duration is

$$T(q) = \frac{1}{Q(q)} = \frac{1}{\lambda(s(q))A(q)}.$$

Substituting into the duration-weighted search contribution gives

$$\begin{aligned} \Delta\varepsilon_w^N &= \lambda_1 E_g\left[\frac{s(q)A(q)D(q)}{\lambda(s(q))A(q)}\right] \\ &= E_g\left[\frac{\lambda_1 s(q)}{\lambda(s(q))}D(q)\right]. \end{aligned} \tag{C.50}$$

Acceptance cancels conditional on the match type: a higher acceptance probability increases the number of quits prevented by a reduction in search but shortens the expected duration preserved by each prevented quit.

If all offers are generated by active search, $\lambda_0 = 0$, the contribution further simplifies to $E_g[D]$. This incumbent-weighted average generally differs from $E_s[D]$, the magnitude of the fixed-composition elasticity of average search, which weights individual responses by baseline search effort.

C.4 Estimating the Elasticity

In the data, match quality q is unobserved. Define

$$\bar{s}^{\text{data}}(w) = \int s(w, q) g(q \mid w) dq \tag{C.51}$$

Assuming the derivative exists,

$$\frac{\partial \bar{s}^{\text{data}}}{\partial \ln[w]} = \int \frac{\partial s(w, q)}{\partial \ln[w]} g(q \mid w) dq + \int s(w, q) \frac{\partial g(q \mid w)}{\partial \ln[w]} dq \tag{C.52}$$

For $\bar{s}^{\text{data}}(w) > 0$, define the search-weighted distribution

$$g_s(q \mid w) = \frac{s(w, q) g(q \mid w)}{\bar{s}^{data}} \tag{C.53}$$

$$\epsilon_w^{\bar{s}^{\text{data}}} = \mathbb{E}_{gs}\left[\epsilon_w^s(w, q)\right] + \frac{1}{\bar{s}^{\text{data}}} \int s(w, q) \frac{\partial g(q \mid w)}{\partial \ln[w]} dq \tag{C.54}$$

C.5 Causal Interpretation of the Average Search Response

Consider a randomized permanent increase of h log points in own-employer pay from a baseline wage w_0, holding outside opportunities and non-pay attributes fixed. Search is measured immediately after treatment, before separations or amenity changes alter current match states. Let $Y_i(h)$ denote realized search under this intervention, with conditional mean $s(w_0 e^h, q)$, and let $g(q)$ be the baseline incumbent distribution. Average search is

$$m(h) \equiv \mathbb{E}[Y_i(h)] = \int s(w_0 e^h, q) g(q)\, dq, \qquad \bar{s} = m(0) > 0. \tag{C.55}$$

Both potential-outcome means refer to the same baseline population.

Let $Z_i \in \{0, 1\}$ indicate randomized treatment assignment and Y_i^{obs} observed search. Under full compliance and no spillovers, the experimental difference in means identifies

$$\Delta m(h) \equiv \mathbb{E}[Y_i^{\text{obs}} \mid Z_i = 1] - \mathbb{E}[Y_i^{\text{obs}} \mid Z_i = 0] = m(h) - m(0). \tag{C.56}$$

Assume that search is positive and differentiable at baseline and that differentiation can be interchanged with integration. Let $\varepsilon_w^s(q)$ denote the state-specific search elasticity at w_0, and define $D(q) = -\varepsilon_w^s(q)$. The search-weighted distribution and its associated expectation are

$$g_s(q) = \frac{s(w_0, q) g(q)}{\bar{s}}, \qquad \mathbb{E}_s[H] = \int H(q) g_s(q)\, dq. \tag{C.57}$$

The local experimental elasticity is

$$\varepsilon_w^{\text{exp}} \equiv \lim_{h \to 0} \frac{\Delta m(h)}{h\,\bar{s}} = \frac{m'(0)}{\bar{s}}. \tag{C.58}$$

Differentiating average search while holding the baseline incumbent distribution fixed gives

$$\varepsilon_w^{\text{exp}} = \frac{1}{\bar{s}} \int \left. \frac{\partial s(w,q)}{\partial \ln w} \right|_{w=w_0} g(q)\,dq. \tag{C.59}$$

Multiplying and dividing the integrand by baseline search $s(w_0, q)$ expresses this response as a weighted average of state-specific elasticities:

$$\varepsilon_w^{\text{exp}} = \int \underbrace{\frac{1}{s(w_0,q)} \left. \frac{\partial s(w,q)}{\partial \ln w} \right|_{w=w_0}}_{\text{State-specific elasticity}} \underbrace{\frac{s(w_0,q)g(q)}{\bar{s}}}_{\text{Search weights}} dq. \tag{C.60}$$

Using the definitions of the search-weighted expectation and $D(q) = -\varepsilon_w^s(q)$, we obtain

$$\varepsilon_w^{\text{exp}} = \mathbb{E}_s[\varepsilon_w^s(q)] = \varepsilon_w^{\bar{s}} = -\mathbb{E}_s[D]. \tag{C.61}$$

The search weights offset the division by baseline search within each state-specific elasticity. Thus, averaging changes in search across workers and dividing by average baseline search is equivalent to averaging individual elasticities with search weights. No additional weighting of experimental observations by search effort is required; an unweighted average of individual elasticities would generally identify a different object.

The mean-response term $\mathbb{E}_s[D]$ in the decomposition is therefore the negative of the causal elasticity of average realized search. A finite pay intervention identifies its finite-change counterpart, converging to this elasticity as $h \to 0$. Even a correctly identified average response is insufficient to determine the contribution of search to stationary employment: that contribution also depends on offer acceptance and the expected duration of the employment relationships preserved.

D Bargaining

In order to understand the relationship between active search and compensation within a framework with renegotiation, I study a simple sequential auction framework with search effort as in Bagger and Lentz (2019). For the sake of exposition, I assume that the unsolicited offer arrival is

small $\lambda_0 \approx 0$ and can thus be ignored.

$$\rho V(q,p) = w(q,p) - c(s) + \delta(U - V(q,p)) \tag{D.1}$$

$$+ \lambda_1 s \left[\int_p^{\bar{p}} \left[V(p,p') - V(q,p) \right] \right] dF(p') \tag{D.2}$$

$$+ \lambda_1 s \left[\int_q^{p} \left[V(p',p) - V(q,p) \right] \right] dF(p') \tag{D.3}$$

The return to a unit of search effort s is then given by

$$\tau = \lambda_1 \left[\int_p^{\bar{p}} \left[V(p,p') - V(q,p) \right] \right] dF(p') + \lambda_1 \left[\int_q^{p} \left[V(p',p) - V(q,p) \right] \right] dF(p') \tag{D.4}$$

Let $\mathbf{x} = (q,p)$ denote the worker's current state and let $z \sim F$ denote the outside draw. Since the search technology is linear, active search shifts the offer-arrival hazard by λ_1. Define the transition map

$$T(\mathbf{x},z) = \begin{cases} (p,z), & z \in (p,\bar{p}], \\ (z,p), & z \in [q,p], \\ (q,p), & z < q. \end{cases}$$

For any observable outcome $y(x)$, define the offer-specific potential gain

$$\Delta Y(z;\mathbf{x}) = y(T(\mathbf{x},z)) - y(\mathbf{x}).$$

Let

$$\mathcal{M}(\mathbf{x}) = (p,\bar{p}], \qquad \mathcal{R}(\mathbf{x}) = [q,p] \tag{D.5}$$

denote the mobility and renegotiation regions, respectively. Moreover, define

$$P_{\mathcal{M}}(\mathbf{x}) = \mathbb{P}[z \in \mathcal{M}(\mathbf{x})], \qquad P_{\mathcal{R}}(\mathbf{x}) = \mathbb{P}[z \in \mathcal{R}(\mathbf{x})] \tag{D.6}$$

The ex ante return to search at state $\mathbf{x}$ is

$$\tau_y(\mathbf{x}) = \lambda_1 \int_{\mathcal{M}(\mathbf{x})} [y(p,z) - y(\mathbf{x})] \, dF(z) + \lambda_1 \int_{\mathcal{R}(\mathbf{x})} [y(z,p) - y(\mathbf{x})] \, dF(z).$$

Equivalently, the ex ante return to search can be written as the weighted sum of the conditional means in both regions

$$\tau_y(\mathbf{x}) = \underbrace{\lambda_1 \mathbb{E}[\Delta Y(z;\mathbf{x})] \mid z \in \mathcal{M}(\mathbf{x}); \mathbf{x}] \mathbb{P}[z \in \mathcal{M}(\mathbf{x})]}_{=\tau^m(\mathbf{x})} + \underbrace{\lambda_1 \mathbb{E}[\Delta Y(z;\mathbf{x})] \mid z \in \mathcal{R}(\mathbf{x}); \mathbf{x}] \mathbb{P}[z \in \mathcal{R}(\mathbf{x})]}_{=\tau^r(\mathbf{x})} \tag{D.7}$$

Econometric Model In the data, I observe search, mobility and outcomes of the current employer-employee match, such as wages, or selected amenities such as working from home. However, I

do not observe $\mathbf{x}$. Nevertheless, it is possible to estimate reduced-form regressions that provide a transparent mapping to the structural parameters of the sequential auction model. Define

$$s_{it}^{m} = \mathbb{1}\{s_{it} = 1, m_{it} = 1\}, \qquad s_{it}^{r} = \mathbb{1}\{s_{it} = 1, m_{it} = 0\}. \tag{D.8}$$

where s^{m} assumes value one if worker i searched in period t and moved employers between t and $t+1$, and s_{it}^{r} assumes value one if the worker searched but did not move. I estimate the following linear regression

$$\Delta y_{it} = \beta_m s_{it}^{m} + \beta_r s_{it}^{r} + \mathbf{Z}_{it}'\mu + \gamma y_{it} + \varepsilon_{it}. \tag{D.9}$$

where Δy_{it} is the change in outcome between t and $t+1$ and $\mathbf{Z}_{it}$ is a vector of time-varying observables. The current level of the outcome y_{it} is included in order to control for selection into search based on transitory, mean-reverting shocks. The error term ϵ_{it} is assumed to satisfy

$$\mathbb{E}[\epsilon_{it} | \mathbf{Z}_{it}, y_{it}, s_{it}^{r}, s_{it}^{m}] = 0 \tag{D.10}$$

To interpret the reduced-form coefficients, I consider a benchmark in which outcome changes in the absence of search-induced offers have conditional mean zero, and the conditional mean gains from mobility and renegotiation do not vary with the included covariates Z_{it} and y_{it}. I abstract from unsolicited offers and multiple offers within the observation period. As before, I drop employer transitions that occur without search from the sample. The omitted category is therefore workers with $s_{it} = 0$ and $m_{it} = 0$, for whom I assume

$$\mathbb{E}[\Delta y_{it} \mid s_{it} = 0, m_{it} = 0, \mathbf{x}] = 0. \quad \forall \mathbf{x} \tag{D.11}$$

Under these assumptions, the population coefficients admit the following conditional-mean interpretation:

$$\beta_m = \int_{\mathbf{x}} \mathbb{E}[\Delta y_{it} \mid s_{it} = 1, m_{it} = 1, \mathbf{x}] dF(\mathbf{x} \mid s_{it} = 1, m_{it} = 1) \tag{D.12}$$

and

$$\beta_r = \int_{\mathbf{x}} \mathbb{E}[\Delta y_{it} \mid s_{it} = 1, m_{it} = 0, \mathbf{x}] dF(\mathbf{x} \mid s_{it} = 1, m_{it} = 0) \tag{D.13}$$

Mobility Note that the mobility indicator returns one if an offer is received and that offer falls in the mobility region.

$$m_{it} = \mathbb{1}[z_{it} \in \mathcal{M}(\mathbf{x})] \mathbb{1}[o_{it} = 1] \tag{D.14}$$

$$\beta_m = \int_{\mathbf{x}} \mathbb{E}[\Delta y_{it} \mid s_{it} = 1, m_{it} = 1, \mathbf{x}] dF(\mathbf{x} \mid s_{it} = 1, m_{it} = 1) \tag{D.15}$$

By Bayes' rule the state distribution among movers who searched actively satisfies

$$dF(\mathbf{x} \mid s_{it} = 1, m_{it} = 1) = \frac{\mathbb{P}[m_{it} = 1 \mid \mathbf{x}, s_{it} = 1]}{\mathbb{P}[m_{it} = 1 \mid s_{it} = 1]} dF(\mathbf{x} \mid s_{it} = 1) \tag{D.16}$$

It follows that

$$\beta_m = \int_x \frac{\tau_y^m(\mathbf{x}) dF(\mathbf{x} \mid s_{it} = 1)}{\lambda_1 \mathbb{E}_x [P_M(\mathbf{x})]} \tag{D.17}$$

Since the denominator is a constant, it follows that

$$\beta_m = \frac{\mathbb{E}_x \left[\tau_y^m(x)\right]}{\lambda_1 \mathbb{E}_x [P_M(x)]}. \tag{D.18}$$

Renegotiation The derivation for the return to search among stayers proceeds in the same way. Define the probability of staying when searching actively

$$P_N(\mathbf{x}) = 1 - \lambda_1 P_M(\mathbf{x}). \tag{D.19}$$

Note that the reduced-form coefficient in equation (D.13) is related to the gain from search (D.7) as follows

$$\beta_r = \int_x \frac{\tau^r(\mathbf{x})}{P_N(\mathbf{x})} dF(\mathbf{x} \mid s_{it} = 1, m_{it} = 0) \tag{D.20}$$

Analogously to (D.16), Bayes' rule implies that the state distribution among stayers who actively searched is given by

$$dF(\mathbf{x} \mid s_{it} = 1, m_{it} = 0) = \frac{\mathbb{P}[m_{it} = 0 \mid \mathbf{x}, s_{it} = 1]}{\mathbb{P}[m_{it} = 0 \mid s_{it} = 1]} dF(\mathbf{x} \mid s_{it} = 1) \tag{D.21}$$

Hence, the reduced-form coefficient satisfies

$$\beta_r = \int_x \frac{\tau^r(\mathbf{x})}{P_N(\mathbf{x})} \frac{P_N(\mathbf{x})}{\mathbb{E}_x [P_N(\mathbf{x})]} dF(\mathbf{x} \mid s_{it} = 1) \tag{D.22}$$

where $\mathbb{E}_x[\cdot]$ is the expectation over $\mathbf{x}$ among searchers prior to mobility being realized. Cancelling terms, the reduced-form coefficient satisfies

$$\beta_r = \frac{\mathbb{E}_x[\tau^r(\mathbf{x})]}{1 - \lambda_1 \mathbb{E}_x [P_M(\mathbf{x})]} \tag{D.23}$$

. The expression states that in order to back out the expected returns to search stemming from renegotiation among searchers, it is sufficient to estimate the reduced-form model in (D.9) and multiply the coefficient on unsuccessful search by the probability of search not translating into an employer transition.

To summarize the relative returns of mobility and renegotiation, it will be useful to compute the ratio of the two channels. Define

$$\pi_M \equiv \mathbb{P}[m_{it} = 1 \mid s_{it} = 1] = \lambda_1 \mathbb{E}_x[P_M(\mathbf{x})] \tag{D.24}$$

The expected probability of moving conditional on search π_M can be estimated from a linear

regression of mobility m_{it} on active search s_{it}. The ratio of the two ex ante returns satisfies

$$\frac{\mathbb{E}_x\left[\tau^m(\mathbf{x})\right]}{\mathbb{E}_x\left[\tau^r(\mathbf{x})\right]} = \frac{\pi_M}{1-\pi_M}\frac{\beta^m}{\beta^r}. \tag{D.25}$$

Thus the ratio of the two channels equals the ratio of reduced-form coefficients multiplied by the odds ratio of switching employers conditional on searching. Note that offer arrival and acceptance rates enter into the expression only via the probability of switching π_M and therefore do not need to be estimated separately.

Estimation I estimate the model in (D.9) using the Swedish Labor Force Survey. I consider four sets of outcomes: i) pay, ii) hours, iii) amenities, and iv) occupational mobility. Broadly speaking, these outcomes reflect the motives for search highlighted in the main text. Throughout, I drop respondents who search due to risk of job loss, contract expiration or who view the current job as temporary. To the extent that precautionary search is an important motive that cannot be met via renegotiation, the analysis provides an upper bound for the extent to which workers generally gain from search via renegotiation. Moreover, I require that individuals do not receive unemployment benefits in the interview year to ensure that employer-employer transitions are measured cleanly.

For pay, I restrict the sample to 2019 and 2020 as administrative data on earnings are available at the monthly level only in these years. Prior to 2019, the matched employer–employee data is at an annual level. The LFS itself does not contain information on wages or earnings. While the restriction to these two years shrinks the sample substantially, it avoids measurement error from time aggregation. I construct wages by dividing monthly earnings by actual hours worked. Since self-reported actual hours worked are noisy, I require that actual hours worked are within 50 percent of usual hours, and truncate the sample at the 5th percentile of the wage distribution.

For hours, I leverage the fact that the LFS asks workers about the additional hours they would desire to work, as well as realized hours in the current job. A key advantage of using hours compared to other outcomes is that the direction and extent of preferences are explicitly encoded in the survey question. I construct two outcomes that capture to what extent hours change in the desired direction. First, I use the change in usual weekly hours between t and $t+1$, divided by the desired number of additional hours that a respondent reports in t. As an alternative, I measure the change in additional hours between t and $t+1$. For both analyses, I restrict the sample to individuals who report that they would like to work at least one more hour and no more than forty hours, and drop observations with more than one hundred hours usually worked in the main job in t and $t+1$.

For amenities, I consider the following set of features: the incidence of shift work, work-from-home, working in the evening, working at night, as well as receiving training on the job. I restrict the sample to observations where the less desirable outcome is realized, that is, I focus on individuals who work night shifts at time t and define the outcome as no longer working shifts at time $t+1$. Given that questions about these amenities are continuously asked in the LFS, and responses are

relatively evenly distributed, the analysis sample for each outcome is generally large.

Lastly, I study the association between search and occupational mobility at the four-digit occupation level. An advantage of using occupational mobility is that information on occupations is collected throughout the LFS, resulting in a large sample that can be used for the analysis. A drawback is that it is unclear whether occupational mobility should be viewed as an unambiguously desirable outcome from the worker's point of view.

Table A.4 reports the resulting estimates.

E Details of the Model

E.1 Unemployed workers.

An unemployed worker is characterized by education e. Her flow payoff is $u_U(e) = b\, a(e)$, and her offer-arrival probability is $\lambda^u(s) = \lambda_0^u + \lambda_1^u s$. If no offer is accepted, the worker remains unemployed. I abstract from transitory acceptance shocks among unemployed workers, so acceptance is determined by continuation values. Conditional on receiving an offer, the expected gain is

$$\Omega^U(e) = \phi_e \mathbb{E}_{\hat{x}} \left[[V(\hat{x}) - U(e)]_+ \,\middle|\, e \right] + (1 - \phi_e) \mathbb{E}_{\hat{q}} \left[[V_O(e, \hat{q}) - U(e)]_+ \right].$$

The choice-specific value of search is consequently

$$W^U(e, s) = u_U(e) - \kappa s + \widetilde{\beta} \left[U(e) + \lambda^u(s) \Omega^U(e) \right]. \tag{E.1}$$

The value of unemployment is

$$U(e) = \mathbb{E}_\epsilon \left[\max_{s \in \{0,1\}} \left\{ W^U(e, s) + \sigma_s \epsilon_s \right\} \right] \tag{E.2}$$

E.2 Contracts.

Jobs differ by contract type. I distinguish permanent, probationary, and fixed-term contracts, and allow permanent employees to enter a state of advance notice. Let $j \in \mathcal{J} \equiv \{P, B, F, N\}$ denote the contract state, where P, B, and F denote permanent, probationary, and fixed-term contracts, respectively, and N denotes advance notice. Whenever the contract state has a deterministic clock, $d \in \{1, \ldots, D_j\}$, where D_j is its maximum duration in months. Duration plays no role for permanent contracts, for which I set $D_P = 1$. As long as a nonpermanent contract state persists and has not reached its terminal duration, its duration evolves deterministically:

$$\Pi^J(j, d+1 \mid j, d) = 1, \qquad j \in \{B, F, N\}, \quad d < D_j. \tag{E.3}$$

Involuntary separations from nonpermanent contract states occur when the state reaches its terminal duration. The separation probability is

$$\delta(\mathbf{x}) = \mathbb{1}\{d = D_j\}\delta_j. \tag{E.4}$$

Since $D_P = 1$, workers on permanent contracts face a direct monthly separation risk $\delta_P > 0$. They may also enter advance notice with monthly probability ϕ_N, conditional on the current match being retained:

$$\Pi^J(N, 1 \mid P, 1) = \phi_N, \qquad \Pi^J(P, 1 \mid P, 1) = 1 - \phi_N. \tag{E.5}$$

Advance notice necessarily ends in separation once the notice period expires, so that $\delta_N = 1$. The contract transition kernel Π^J is defined conditional on the current match being retained. At the expiration of a temporary contract, $j \in \{B, F\}$, the retained worker either converts to a permanent contract or renews the existing contract:

$$\Pi^J(j', d' \mid j, D_j) = \begin{cases} \phi_j^c, & \text{if } (j', d') = (P, 1), \\ \phi_j^r, & \text{if } (j', d') = (j, 1), \end{cases} \qquad \phi_j^c + \phi_j^r = 1. \tag{E.6}$$

Thus, the corresponding unconditional probabilities of separation δ_j, conversion $(1 - \delta_j)\phi_j^c$, and renewal $(1 - \delta_j)\phi_j^r$ sum to one.

E.3 Employment outside the ranked sector

The empirical analysis assigns a firm rank only to workers employed at firms in the estimation sample. The model therefore distinguishes between employment in the ranked sector, denoted by I, employment outside the ranked sector, denoted by O, and unemployment, denoted by U. The outside sector includes public-sector employment as well as employment at private-sector firms excluded from the ranked-firm sample because of industry or data restrictions. Thus, outside employment differs from ranked employment in flow payoff and separation risk. Match-specific amenities q follow the same stochastic process as in the inside sector. Moreover, the search technology is identical across sectors. Random search implies that conditional on education, agents in the outside sector face the same offer distribution.

State and flow payoff. An outside job is characterized by the worker's education e and a match-specific amenity q:

$$z_O = (e, q). \tag{E.7}$$

The flow payoff from outside employment is

$$u_O(e, q) = o_e + q, \tag{E.8}$$

where o_e captures the education-specific average value of characteristics omitted from the outside-sector state space. In particular, outside jobs do not carry a firm rank, contract type, contract duration, hours state, or advance-notice state.

Bellman equations An outside job separates exogenously into unemployment with monthly probability δ_O. If no offer is accepted, separation is realized before the incumbent match-quality transition. The value of rejecting an offer, prior to the realization of separation, is

$$V_O^R(e, q) = \delta_O U(e) + (1 - \delta_O)\mathbb{E}_{q'}\left[V_O(e, q')\right] \tag{E.9}$$

Thus, an accepted offer replaces both the incumbent separation risk and the incumbent match-quality transition. Let $c(s)$ denote the contemporaneous search cost. The choice-specific value of an outside worker is

$$W_O(e, q, s) = o_e + q - c(s) + \tilde{\beta}\lambda(s)\Omega_O(e, q) + \tilde{\beta}V_O^R(e, q) \tag{E.10}$$

The outside-employment value $V_O(e, q)$ and the search probability are obtained by applying the same logit search-choice operator used elsewhere in the model to the two choice-specific values in equation (E.10).

$$\Omega_O(e, q) = \phi_e \mathbb{E}_\eta\left[\mathbb{E}_{\hat{x}}\left[\max\left\{V(\hat{\mathbf{x}}) - V_O^R(e, q) + \sigma_o\eta_1, \sigma_o\eta_0\right\} \mid e\right]\right] \tag{E.11}$$

$$+ (1 - \phi_e)\mathbb{E}_\eta\left[\mathbb{E}_{\hat{q}}\left[\max\left\{V_O(e, \hat{q}) - V_O^R(e, q) + \sigma_o\eta_1, \sigma_o\eta_0\right\}\right]\right] \tag{E.12}$$

E.4 Stationary distribution

Let the state relevant to search decisions be given by

$$z = x \tag{E.13}$$

In the retention and tenure calculations below, z and z' denote inside-sector states. Define the probability of search action s as

$$p(s, z) = \mathbb{P}[s_t = s \mid x_t = z] \tag{E.14}$$

for any $s \in \{0, 1\}$. The probability of actively searching which solves the system of Bellman equations is given in equation (22). Write

$$p_1(z) = p(1, z) \quad p_0(z) = 1 - p_1(z) \tag{E.15}$$

Define retention r_t as an indicator that assumes value one if an agent starts period $t + 1$ with the same employer as in period t. Retention nests contract renewal and conversion. Events that trigger

$r_t = 0$ are layoffs, labor market exit and employer-to-employer transitions, including to employers of the same firm type. Define the transition kernel conditional on retention as

$$\Pi^r(x' \mid x) = \mathbb{P}[x_{t+1} = x' \mid x_t = x, r_t = 1] \tag{E.16}$$

Conditional on the current state, offer acceptance is independent of the search action. The transition kernel conditional on retention is likewise independent of the current search action.

The probability that a worker is retained satisfies

$$\rho(z, s) = (1 - \mu)(1 - \lambda(s)A(z))(1 - \delta(z)) \tag{E.17}$$

Retention requires: i) that no labor market exit takes place, ii) that no acceptable offer is received, and iii) that, conditional on i) and ii), no exogenous separation takes place. The probability that a state transition from z to z' is associated with retention is given by

$$\Gamma(z, z') = \sum_{s \in \{0,1\}} p(s, z)\, \rho(z, s)\, \Pi^r(z' \mid z). \tag{E.18}$$

Since the retention probability is always weakly less one, the rows of Γ must sum to weakly less than one

$$\Gamma \mathbf{1} \leqslant \mathbf{1}. \tag{E.19}$$

Missing row mass corresponds to labor-market exit, separation, or an employer transition. Thus, Π^r governs state evolution conditional on same-employer retention, while Γ propagates employer tenure. The factor $1 - \mu$ is included in Γ because labor-market exit ends the current employer-tenure spell.

Stationary Distribution Define the total state space $\mathcal{Z} = \mathcal{Z}_I \cup \mathcal{Z}_U \cup \mathcal{Z}_O$, where

$$\mathcal{Z}_I = \{I, e, y, h, w, j, d, q\} \quad \mathcal{Z}_U = \{e\} \quad \mathcal{Z}_O = \{O, e, q\} \tag{E.20}$$

Let Π^0 denote the transition matrix on $\mathcal{Z}$ conditional on no labor-market exit. Its block form is

$$\Pi^0 = \begin{bmatrix} \Pi^0_{II} & \Pi^0_{Iu} & \Pi^0_{IO} \\ \Pi^0_{uI} & \Pi^0_{uu} & \Pi^0_{uO} \\ \Pi^0_{OI} & \Pi^0_{Ou} & \Pi^0_{OO} \end{bmatrix} \tag{E.21}$$

Moreover, define

$$\nu = (0, \nu_u, 0) \quad \nu_u(e) = \nu_e(e) \tag{E.22}$$

which satisfies $\nu \mathbb{1} = 1$, since all entrants must be allocated to some state. The full transition matrix is given by

$$\Pi = (1 - \mu)\Pi^0 + \mu \mathbf{1} \nu \tag{E.23}$$

Let $G = (G_I, G_U, G_O)$ denote the stationary distribution over the complete state space. By definition, it satisfies

$$G = G\Pi \qquad G\mathbf{1} = 1 \tag{E.24}$$

Stationary Distribution of Tenure Let G_I denote the inside-sector block of the stationary distribution G, and let H_τ denote the unconditional stationary mass in inside-sector states with employer tenure exactly equal to τ months. By construction,

$$G_I = \sum_{\tau=1}^{\infty} H_\tau. \tag{E.25}$$

Every inside-sector worker is either at tenure one or was retained by the same employer from the preceding month. Stationarity therefore gives

$$G_I = H_1 + G_I\Gamma, \tag{E.26}$$

and hence

$$H_1 = G_I(I - \Gamma). \tag{E.27}$$

Stationarity implies that, for every state z, total inflows equal total outflows. Equivalently, $G_I(I - \Gamma)$ gives the inflow into inside-sector states associated with a new employer match. For an expiring temporary-contract state, this inflow is zero, since all new matches begin at duration $d = 1$. Its stationary mass is therefore generated entirely by within-employer transitions from earlier-duration states. The tenure distribution then evolves mechanically by applying the retention matrix

$$H_{\tau+1} = H_\tau\Gamma \tag{E.28}$$

Hence, the full tenure distribution can be obtained

$$H_\tau = G_I(I - \Gamma)\Gamma^{\tau-1} \quad \forall \tau \in \mathbb{N}_+ \tag{E.29}$$

It is useful to note that the unconditional stationary mass in inside-sector states associated with tenure of at least $\bar{\tau}$ months is

$$H_{\geqslant\bar{\tau}} = G_I\Gamma^{\bar{\tau}-1}. \tag{E.30}$$

E.5 Decomposition of Search Contribution in Discrete Time.

Let $p(x) = p(1, x)$ denote the probability of active search at incumbent state x, and write $\lambda(p(x)) = \lambda_0 + \lambda_1 p(x)$. Conditional on the state, offer acceptance is independent of the search action. The same-employer retention kernel is therefore

$$\Gamma(x, dx') = (1 - \mu)(1 - \delta(x))\big[1 - \lambda(p(x))A(x)\big]\Pi(dx' \mid x). \tag{E.31}$$

Here Π describes the evolution of contract and amenity states conditional on retaining the employer and is independent of the current search action.

Let r denote the measure of new hires and n the stationary incumbent measure at the focal employer. Then

$$n = r + n\Gamma, \qquad N = n\mathbf{1}, \qquad T = (I - \Gamma)^{-1}\mathbf{1}. \tag{E.32}$$

Assuming expected durations are finite, $T(x)$ is the expected number of months remaining with the employer, including the current month. Write $g = n/N$ for the incumbent distribution.

Compare endogenous search with a policy that freezes the baseline search decision at each state and search-shock realization, while allowing offer acceptance to adjust. The envelope argument equates the local value, acceptance, and recruitment derivatives in the two cases. Holding μ, δ, Π, and outside opportunities fixed, define

$$D(x) = -\frac{\partial \ln p(x)}{\partial \ln w}.$$

Differentiating the stationary employment equation and subtracting the frozen-search response gives

$$\Delta\varepsilon_w^N = \lambda_1 \mathbb{E}_g \left[p(x) A(x) D(x) (1-\mu)(1-\delta(x))(\Pi T)(x) \right], \tag{E.33}$$

where

$$(\Pi T)(x) = \int T(x')\Pi(dx' \mid x).$$

All objects are evaluated at the common baseline.

The factor $(1-\mu)(1-\delta(x))(\Pi T)(x)$ measures the expected future employment preserved by preventing an accepted offer. Current employment has already occurred, and the worker must avoid labor-market exit and the subsequent layoff risk before continuing with the employer next month.

For the corresponding three-term decomposition, define

$$Q(x) = (1-\mu)\lambda(p(x))A(x), \qquad S(x) = 1 - (\Gamma\mathbf{1})(x),$$

and

$$\bar{Q} = \mathbb{E}_g[Q], \qquad \bar{S} = \mathbb{E}_g[S], \qquad \theta^Q = \frac{(1-\mu)\lambda_1 \mathbb{E}_g[pA]}{\bar{Q}}.$$

Let $\mathbb{E}_p$ and $\mathbb{E}_{pA}$ denote expectations under incumbent weights proportional to p and pA, respectively. Equation (E.33) becomes

$$\begin{aligned} \Delta\varepsilon_w^N = \theta^Q \frac{\bar{Q}}{\bar{S}} \Bigg\{ & \mathbb{E}_p[D] + \frac{\mathrm{Cov}_p(A, D)}{\mathbb{E}_p[A]} \\ & + \mathbb{E}_{pA}\left[D(x) \left\{ \bar{S}(1-\delta(x))(\Pi T)(x) - 1 \right\} \right] \Bigg\}. \end{aligned} \tag{E.34}$$

Unlike its continuous-time counterpart, the final term captures both differences in remaining duration and the within-month timing of competing separation risks.

F Identification

F.1 Offer Arrival

Let $f(s)$ denote the probability that an employed worker switches jobs conditional on her search status s. Let $A(s)$ denote the expected acceptance probability conditional on search status s, and let

$$p = \mathbb{P}[s = 1]$$

denote the share of employed workers who search.

Define $\bar{f}$ as the unconditional job-to-job transition rate and $\bar{A}$ as the acceptance probability among offers received by employed workers. It must hold in aggregate that

$$\bar{f} = \bar{A}\left(\lambda_0 + p\lambda_1\right). \tag{F.1}$$

Conditional on observing the aggregate job-transition rate and the average acceptance rate, the total offer-arrival rate can therefore be recovered as

$$\lambda_0 + p\lambda_1 = \frac{\bar{f}}{\bar{A}}. \tag{F.2}$$

Conditional transition rates satisfy

$$A(0) = \frac{f(0)}{\lambda_0}, \qquad A(1) = \frac{f(1)}{\lambda_0 + \lambda_1}. \tag{F.3}$$

Let θ_e denote the active-hire share, defined as the share of employment-to-employment transitions generated through the active-search channel:

$$\theta_e = \frac{p\lambda_1 A(1)}{\bar{f}}. \tag{F.4}$$

Substituting for $A(1)$ using (F.1) yields

$$\theta_e = \frac{pf(1)}{\bar{f}} \frac{\lambda_1}{\lambda_0 + \lambda_1}. \tag{F.5}$$

Define

$$\chi \equiv \frac{\theta_e \bar{f}}{p f(1)}. \tag{F.6}$$

Equation (F.5) implies

$$\chi = \frac{\lambda_1}{\lambda_0 + \lambda_1}. \tag{F.7}$$

Thus, χ identifies the fraction of offers received by active searchers that are generated through active search. Equivalently,

$$\frac{\lambda_1}{\lambda_0} = \frac{\chi}{1-\chi}. \tag{F.8}$$

Combining (F.7) with the aggregate contact rate in (F.2) gives

$$\lambda_0 = \left(\frac{1-\chi}{1-\chi+p\chi}\right)\left(\frac{\bar{f}}{\bar{A}}\right), \qquad \lambda_1 = \left(\frac{\chi}{1-\chi+p\chi}\right)\left(\frac{\bar{f}}{\bar{A}}\right). \tag{F.9}$$

Using the definition of χ, these expressions may equivalently be written entirely as a function of parameters $\{\bar{f}, \bar{A}, p, f(1), \theta_e\}$. Except for $\bar{A}$, each parameter is observed in the Swedish data.

F.2 Unemployed Search Technology

Let s_u denote the share of unemployed workers who search. Offers can arrive through two distinct and mutually exclusive channels. A passive, or unsolicited, offer arrives with probability λ_0^u. Conditional on active search, an actively generated offer arrives with probability λ_1^u. Thus,

$$\lambda^u(s_u) = \lambda_0^u + \lambda_1^u s_u \tag{F.10}$$

Let $A_u(0)$ and $A_u(1)$ denote the probabilities that an offer is accepted by an inactive and active unemployed worker, respectively. Because passive and active offers are drawn from the same offer distribution, the source of an offer does not directly affect its probability of acceptance. Therefore, the average job-finding rate $f_u \in (0,1)$ satisfies

$$f_u = (1-s_u)\lambda_0^u A_u(0) + s_u(\lambda_0^u + \lambda_1^u)A_u(1) \tag{F.11}$$

The active hire share, defined as the share of hires from unemployment generated through the active search channel, is given by

$$\theta_u = \frac{s_u \lambda_1^u A_u(1)}{f_u} \tag{F.12}$$

For identification, I assume that the unemployed accept all offers $A_u(0) = A_u(1) = 1$. This restriction is not mechanically imposed in the structural Bellman problem. Instead, I assess its internal consistency after estimation using the model-implied acceptance probabilities of

unemployed workers. The assumption implies that the offer arrival parameters are given by

$$\lambda_0^u = (1 - \theta_u) f_u \qquad \lambda_1^u = \frac{\theta_u f_u}{s_u}. \tag{F.13}$$

Hence, the unemployed search rate, job-finding rate, and active hire share, all of which can be estimated from the data, jointly identify the passive and active components of the unemployed offer arrival technology.

F.3 Search across Firms and Match Heterogeneity.

Holding other worker and job characteristics fixed, let $v(y, q)$ denote the expected gain from search before the recurring cost κ. The probability of search satisfies

$$P(y, q) = \Lambda\left(\frac{v(y, q) - \kappa}{\sigma_s}\right), \tag{F.14}$$

where Λ is the logistic distribution function and $\sigma_s > 0$ is the scale of the transitory search-choice shocks.

Let $g(q \mid y)$ denote the density of match amenities among employed workers conditional on firm type y. The average search probability at firm type y is

$$p(y) = \int_{\mathcal{Q}} P(y, q) g(q \mid y)\, dq. \tag{F.15}$$

Assume that P and g are differentiable in y, that g is positive on a common support $\mathcal{Q}$, and that differentiation can be interchanged with integration. Then

$$p'(y) = \int_{\mathcal{Q}} P_y(y, q) g(q \mid y)\, dq + \int_{\mathcal{Q}} P(y, q) g_y(q \mid y)\, dq. \tag{F.16}$$

The first term captures the response of search holding match amenities fixed. The second captures changes in the composition of incumbent matches across firm types.

The logit policy implies

$$P_y(y, q) = \frac{1}{\sigma_s} P(y, q)[1 - P(y, q)] v_y(y, q). \tag{F.17}$$

Consequently,

$$p'(y) = \frac{1}{\sigma_s} \mathbb{E}\left[P(y, q)[1 - P(y, q)] v_y(y, q) \mid y\right] + S(y), \tag{F.18}$$

where

$$S(y) \equiv \int_{\mathcal{Q}} P(y, q) g_y(q \mid y)\, dq. \tag{F.19}$$

All conditional expectations below are taken with respect to $g(q \mid y)$.

Selection. Since $g(q \mid y)$ is a conditional density,

$$\int_{\mathcal{Q}} g(q \mid y)\, dq = 1$$

for every $y \in \mathcal{Y}$. Differentiating this normalization gives

$$\int_{\mathcal{Q}} g_y(q \mid y)\, dq = 0. \tag{F.20}$$

Moreover,

$$\partial_y \log g(q \mid y) = \frac{g_y(q \mid y)}{g(q \mid y)}.$$

It follows that the log-density derivative has conditional mean zero:

$$\begin{aligned} \mathbb{E}\left[\partial_y \log g(q \mid y) \mid y\right] &= \int_{\mathcal{Q}} \frac{g_y(q \mid y)}{g(q \mid y)} g(q \mid y)\, dq \\ &= \int_{\mathcal{Q}} g_y(q \mid y)\, dq = 0. \end{aligned} \tag{F.21}$$

Substituting $g_y(q \mid y) = g(q \mid y)\partial_y \log g(q \mid y)$ into equation (F.19) therefore yields

$$\begin{aligned} S(y) &= \mathbb{E}\left[P(y,q)\partial_y \log g(q \mid y) \mid y\right] \\ &= \mathrm{Cov}\left(P(y,q), \partial_y \log g(q \mid y) \mid y\right). \end{aligned} \tag{F.22}$$

Since the second variable in the covariance has conditional mean zero, and $\mathbb{E}[P(y,q) \mid y] = p(y)$, we can equivalently write

$$\begin{aligned} S(y) &= \mathbb{E}\left[[P(y,q) - p(y)]\partial_y \log g(q \mid y) \mid y\right] \\ &= \int_{\mathcal{Q}} [P(y,q) - p(y)] \frac{g_y(q \mid y)}{g(q \mid y)} g(q \mid y)\, dq \\ &= \int_{\mathcal{Q}} [P(y,q) - p(y)] g_y(q \mid y)\, dq. \end{aligned} \tag{F.23}$$

The same expression follows directly from equation (F.20), since subtracting $p(y)$ from the search propensity does not change the integral. The selection term is positive when higher firm types place greater weight on matches with above-average search propensities and less weight on matches with below-average search propensities. In this case, selection offsets a negative response of search to firm type holding amenities fixed. Its sign is not imposed by the decomposition.

Heterogeneity in search propensities. Define the share of search variation attributable to differences in search propensities across amenities as

$$\omega(y) \equiv \frac{\mathrm{Var}[P(y,q) \mid y]}{p(y)[1 - p(y)]}. \tag{F.24}$$

Because search is binary, its conditional variance is $p(y)[1-p(y)]$. The law of total variance gives

$$p(y)[1-p(y)] = \text{Var}[P(y,q) \mid y] + \mathbb{E}\left[P(y,q)[1-P(y,q)] \mid y\right]. \tag{F.25}$$

Hence $0 \leqslant \omega(y) \leqslant 1$, and

$$\mathbb{E}\left[P(y,q)[1-P(y,q)] \mid y\right] = p(y)[1-p(y)][1-\omega(y)]. \tag{F.26}$$

Let

$$\bar{v}_y^M(y) \equiv \frac{\mathbb{E}\left[P(y,q)[1-P(y,q)]v_y(y,q) \mid y\right]}{\mathbb{E}\left[P(y,q)[1-P(y,q)] \mid y\right]} \tag{F.27}$$

denote the average gain gradient, weighted by $P(y,q)[1-P(y,q)]$. These weights give greater importance to states in which search choices are more responsive to a change in the gain from search. No restriction that $v_y(y,q)$ is common across amenity states is required.

Combining equations (F.18)–(F.27) gives

$$p'(y) = \frac{\bar{v}_y^M(y)}{\sigma_s} p(y)[1-p(y)][1-\omega(y)] + S(y). \tag{F.28}$$

Finally, let $\ell(p) = \log[p/(1-p)]$ denote log odds. Since

$$\frac{d\ell[p(y)]}{dy} = \frac{p'(y)}{p(y)[1-p(y)]},$$

the aggregate search gradient satisfies

$$\frac{d\ell[p(y)]}{dy} = \frac{\bar{v}_y^M(y)}{\sigma_s}[1-\omega(y)] + \frac{S(y)}{p(y)[1-p(y)]}. \tag{F.29}$$

The decomposition separates responsiveness within amenity states, aggregation over heterogeneous search propensities, and selection across firm types. For a given gain schedule, σ_s governs the response of conditional search log odds. At a given weighted gain gradient, heterogeneity in search propensities attenuates the behavioral component of the aggregate log-odds gradient through the factor $1-\omega(y)$. Changes in match composition contribute the selection term, which can either offset or reinforce that component.

F.4 Search and Employer Tenure.

To isolate the role of within-match amenity changes, consider a stationary benchmark with fixed non-amenity job and worker characteristics. Abstract from contract transitions and let δ denote a constant monthly separation probability. Let $p(q)$ denote the probability of search conditional on the current amenity, and let $A(q)$ denote the probability of accepting an offer conditional on receiving one. Current search affects offer arrival but not acceptance conditional on the offer. Averaging over the search decision, the probability of remaining with the same employer in the

following month is

$$r(q) = (1-\mu)(1-\delta)\{1-[\lambda_0+\lambda_1 p(q)]A(q)\}. \tag{F.30}$$

Retention requires that the worker does not exit the labor market, does not accept another job, and does not experience an exogenous separation.

Let $g_\tau(q)$ denote the density of amenities among workers with employer tenure τ, measured at the beginning of the month. Their average search and retention probabilities are

$$\bar{p}_\tau = \int p(q) g_\tau(q)\, dq, \qquad \bar{r}_\tau = \int r(q) g_\tau(q)\, dq. \tag{F.31}$$

Define the average search propensity following an independent amenity draw as

$$\bar{p}_F = \int p(q)\, dF_q(q). \tag{F.32}$$

This quantity averages over the amenity redraw distribution rather than the selected distribution of amenities among accepted matches.

The amenity distribution at tenure $\tau+1$ reflects both selective retention and within-match amenity changes. Before the amenity transition, the density among retained workers is $r(q)g_\tau(q)/\bar{r}_\tau$. A fraction $1-\zeta$ of these workers retain their current amenity, while a fraction ζ receive an independent draw from F_q, with density f_q. Consequently,

$$g_{\tau+1}(q) = (1-\zeta)\frac{r(q)g_\tau(q)}{\bar{r}_\tau} + \zeta f_q(q). \tag{F.33}$$

Multiplying by the search propensity gives

$$p(q)g_{\tau+1}(q) = (1-\zeta)\frac{p(q)r(q)g_\tau(q)}{\bar{r}_\tau} + \zeta p(q) f_q(q). \tag{F.34}$$

Integrating over amenities yields the average search probability at tenure $\tau+1$:

$$\bar{p}_{\tau+1} = (1-\zeta)\frac{\mathbb{E}_\tau[p(q)r(q)]}{\bar{r}_\tau} + \zeta \bar{p}_F, \tag{F.35}$$

where $\mathbb{E}_\tau$ denotes expectation under g_τ. Using the covariance identity

$$\mathbb{E}_\tau[p(q)r(q)] = \bar{p}_\tau \bar{r}_\tau + \mathrm{Cov}_\tau(p,r),$$

and subtracting $\bar{p}_\tau$, we obtain

$$\bar{p}_{\tau+1} - \bar{p}_\tau = \zeta(\bar{p}_F - \bar{p}_\tau) + (1-\zeta)\frac{\mathrm{Cov}_\tau(p,r)}{\bar{r}_\tau}. \tag{F.36}$$

The tenure profile therefore reflects two forces. Amenity redraws move average search toward $\bar{p}_F$. Selective retention changes the relative weight of matches with different search propensities.

When matches with higher search propensities are less likely to survive, $\mathrm{Cov}_\tau(p, r) < 0$, so selection lowers average search among the surviving matches. Amenity redraws counteract this selection whenever $\bar{p}_F > \bar{p}_\tau$.

Suppose that the tenure-specific search and retention means and their covariance converge as $\tau \to \infty$, with $\bar{r}_\infty > 0$. Taking limits in equation (F.36) gives

$$\zeta(\bar{p}_F - \bar{p}_\infty) = -(1-\zeta)\frac{\mathrm{Cov}_\infty(p, r)}{\bar{r}_\infty}. \tag{F.37}$$

At long tenures, the effect of amenity redraws on average search must therefore offset the effect of selective retention. A flat tenure profile does not imply that either process has stopped; it implies that their effects on average search balance. Conditional on the search and acceptance blocks and the amenity draw distribution, the level of search among durable matches therefore provides information about the redraw probability ζ. The limiting distribution and covariance are themselves endogenous, so this relationship explains the information supplied by the tenure moment rather than providing a separate estimator of ζ.

The preceding derivation accounts for selective retention within continuing employment relationships. To isolate persistence generated by amenities alone, I now consider the stationary amenity process, abstracting from selective retention. Amenities follow the stationary distribution F_q, and transitory search-choice shocks are independent over time conditional on amenities.

$$p(q) = \mathbb{P}(s = 1 \mid q_t = q) \tag{F.38}$$

$$\bar{p}_F = \mathbb{E}_{F_q}[p(q)] \tag{F.39}$$

The probability that no reset occurs between $t + k$ and t is equal to $(1-\zeta)^k$, in which case $q_{t+k} = q_t$. Due to the conditional independence assumption,

$$\mathbb{E}[p(q_{t+k}) \mid q_t] = (1-\zeta)^k p(q_t) + [1 - (1-\zeta)^k]\bar{p}_F \tag{F.40}$$

for $k \geqslant 1$.

$$\mathbb{E}[s_t s_{t+k} \mid q_t, q_{t+k}] = p(q_t)p(q_{t+k}) \tag{F.41}$$

Taking expectations yields

$$\mathbb{E}[s_t s_{t+k}] = \mathbb{E}\left[p(q_t)\mathbb{E}[p(q_{t+k}) \mid q_t]\right] \tag{F.42}$$

Using the previous result gives

$$p(q_t)\mathbb{E}[p(q_{t+k}) \mid q_t] = (1-\zeta)^k p(q_t)^2 + [1 - (1-\zeta)^k]p(q_t)\bar{p}_F \tag{F.43}$$

$$\mathbb{E}[s_t s_{t+k}] = (1-\zeta)^k \mathbb{E}\left[p(q_t)^2\right] + [1-(1-\zeta)^k]\bar{p}_F^2 \tag{F.44}$$

As long as s_t is stationary, $\mathbb{E}[s_t] = \mathbb{E}[s_{t+k}] = \bar{p}_F$. Subtracting $\bar{p}_F^2$ from both sides yields

$$\mathrm{Cov}(s_t, s_{t+k}) = (1-\zeta)^k \mathrm{Var}_{F_q}(p(q)) \tag{F.45}$$

If search is stationary,

$$\mathrm{Var}(s_t) = \mathrm{Var}(s_{t+k}) = \bar{p}_F(1-\bar{p}_F) \tag{F.46}$$

It follows that

$$\rho_k = (1-\zeta)^k \frac{\mathrm{Var}_{F_q}(p(q))}{\bar{p}_F(1-\bar{p}_F)} \tag{F.47}$$

$$\bar{p}_F\,(1-\bar{p}_F) = \underbrace{\mathrm{Var}_{F_q}[p(q)]}_{\text{Heterogeneity in search propensities}} + \underbrace{\mathbb{E}_{F_q}[p(q)\,(1-p(q))]}_{\text{Transitory choice variation}}. \tag{F.48}$$

Define

$$\omega_F = \frac{\mathrm{Var}_{F_q}[p(q)]}{\bar{p}_F(1-\bar{p}_F)}, \qquad \rho_k = (1-\zeta)^k \omega_F. \tag{F.49}$$

Among continuing employment relationships, selective retention generally implies that observed search persistence differs from this benchmark.

F.5 Advance Notice

Among workers on permanent contracts, unemployment can arise from direct separation or from the expiration of advance notice. All probabilities and expectations below condition on initial employment in a permanent or advance-notice state and on labor-force survival. For binary s_{it}, the covariance identity gives

$$\mathbb{P}[U_{it+1}{=}1 \mid s_{it}{=}1] - \mathbb{P}[U_{it+1}{=}1 \mid s_{it}{=}0] = \left(\mathbb{P}[s_{it}{=}1 \mid U_{it+1}{=}1] - \mathbb{P}[s_{it}{=}1]\right) \frac{\mathbb{P}[U_{it+1}{=}1]}{\mathbb{V}[s_{it}]}. \tag{F.50}$$

The monthly probability of entering unemployment conditional on current search satisfies

$$\mathbb{P}[U_{i,t+1} = 1 \mid s_{it} = s] = \mathbb{E}\left[\left(1-\lambda(s)A(\mathbf{x}_{it})\right)\delta(\mathbf{x}_{it}) \,\middle|\, s_{it} = s\right]. \tag{F.51}$$

Here $A(\mathbf{x})$ is the probability of accepting an offer conditional on receiving one. Within the permanent-contract population, $\delta(\mathbf{x}) = \delta_P$ for workers in state P, equals one at the terminal duration of advance notice, and is zero in earlier notice months. The factor $1-\lambda(s)A(\mathbf{x})$ accounts for the possibility that an accepted offer avoids separation from the incumbent job into unemployment.

The notice-entry probability ϕ_N affects these transition rates through the stationary distribution of notice states and workers' incentives to search before separation. The unemployment transition rates of searchers and nonsearchers therefore jointly discipline δ_P and ϕ_N, conditional on the remaining model parameters. The model counterparts are evaluated over the same quarterly

interval as the data. The covariance identity describes the association between active search and subsequent unemployment, it does not by itself provide a separate inversion for ϕ_N.

F.6 Expiry probabilities of temporary contracts

The contract kernel leaves two free parameters per temporary type $j \in \{B, F\}$: the terminal separation probability δ_j and the conversion share ϕ_j^c, with $\phi_j^r = 1 - \phi_j^c$. It is convenient to work with the unconditional expiry splits

$$\pi_j^c \equiv (1 - \delta_j)\,\phi_j^c, \qquad \pi_j^r \equiv (1 - \delta_j)\,\phi_j^r, \qquad \pi_j^c + \pi_j^r + \delta_j = 1, \tag{F.52}$$

and to impose $\phi_B^r = 0$: probationary contracts are not renewed. The block therefore has three free parameters, $(\delta_B, \delta_F, \phi_F^c)$.

Flows at expiry. At its terminal duration, the cohort of contract-j workers faces the trinomial lottery $(\pi_j^c, \pi_j^r, \delta_j)$. Two of the three outcomes generate observable worker flows: conversion produces a same-employer transition into a permanent contract, and termination a transition into unemployment—for temporary contracts the only channel into unemployment. Renewal generates no flow: a same-firm, same-type continuation is indistinguishable from an unbroken spell. Let ξ_j denote the share of the contract-j stock at its terminal duration, an equilibrium object determined by the stationary duration distribution and of order $1/D_j$. Conditional on labor-force survival, the share of contract-j workers exposed to the expiry lottery is

$$\eta_j = \xi_j \mathbb{E}\left[1 - \lambda(s_t) A(\mathbf{x}_t) \,\middle|\, j_t = j,\ d_t = D_j\right]. \tag{F.53}$$

The expectation averages over current states and search decisions within the terminal-duration cohort. The monthly conversion and termination rates out of the stock are therefore

$$m_j^c = \eta_j \pi_j^c, \qquad m_j^u = \eta_j \delta_j. \tag{F.54}$$

Identification. Both flows scale with the same terminal cohort, so their ratio identifies the split free of any equilibrium object:

$$\frac{m_j^c}{m_j^u} = \frac{\pi_j^c}{\delta_j}. \tag{F.55}$$

For probationary contracts, $\pi_B^r = 0$ supplies the adding-up condition $\pi_B^c + \delta_B = 1$, and (F.55) closes the block with no further input:

$$\delta_B = \frac{m_B^u}{m_B^c + m_B^u}, \tag{F.56}$$

the termination share among observed expiry outcomes. For fixed-term contracts, the ratio leaves one dimension free; the level of either flow supplies the scale, $\pi_F^c = m_F^c/\eta_F$ and $\delta_F = m_F^u/\eta_F$, with η_F computed from the model's stationary duration distribution and offer-acceptance probabilities.

The renewal probability $\pi_F^r = 1 - (m_F^c + m_F^u)/\eta_F$ is the residual claimed by neither observed expiry flow, since renewal generates neither conversion nor termination.

Feasibility, $m_j^c + m_j^u \leqslant \eta_j \leqslant \xi_j$, holds in the model by construction. Because search intensifies as expiry approaches, both the duration distribution and the probability of reaching the expiry lottery respond to the contract parameters through behavior. The ratio of monthly conversion and termination flows is unaffected by their common exposure term, while the levels are resolved jointly in estimation.

Measurement. The data counterparts are quarterly: $\hat{\Phi}_j^c$, the probability that a worker observed in contract j is observed with the same employer in a permanent contract at the next interview, and $\hat{\Phi}_j^u$, the probability that she is observed unemployed. The model counterparts apply the identical measurement function to the simulated survey panel; the mappings (F.55)–(F.56) locate the information content of the moments and are not used as estimators. The interaction of expiry with same-month quits and exits of the terminal cohort is a product of small probabilities that the simulated measurement resolves exactly under the timing convention of Section 5.1.

F.7 Outside-Sector Values

Let $z_I = x_I$ denote the state of an inside-sector job with characteristics x_I. Let $s \in \{0, 1\}$ denote the worker's current search action. For an outside-sector offer with characteristics x_O, let

$$z_O = x_O$$

denote the state that the worker enters upon accepting the offer.

Let $V_O(\cdot)$ denote the value function of outside-sector jobs. Let $V_I^R(z_I)$ denote the value of remaining in the inside-sector job, prior to the resolution of uncertainty concerning the evolution of the incumbent match. When making a binary choice between remaining in an inside-sector job and accepting an outside-sector offer, the acceptance probability satisfies

$$A_{IO}(z_O, z_I) = \Lambda\left(\frac{V_O(z_O) - V_I^R(z_I)}{\sigma_O}\right). \tag{F.57}$$

Because the two shocks have common scale σ_O, taking log odds of the logit acceptance probability gives

$$V_O(z_O) = V_I^R(z_I) + \sigma_O \ell\left[A_{IO}(z_O, z_I)\right]. \tag{F.58}$$

Taking expectations over outside-sector offer characteristics conditional on z_I and s gives

$$\mathbb{E}\left[V_O(z_O) \mid z_I\right] = V_I^R(z_I) + \sigma_O \mathbb{E}\left[\ell\left[A_{IO}(z_O, z_I)\right] \mid z_I\right]. \tag{F.59}$$

Because outside-sector offer characteristics are drawn randomly conditional on education,

$$x_O \perp z_I \mid e,$$

and hence

$$\mathbb{E}\left[V_O(z_O) \mid e, s\right] = V_I^R(z_I) + \sigma_O \mathbb{E}\left[\ell\left[A_{IO}(z_O, z_I)\right] \mid z_I\right]. \tag{F.60}$$

Now let $p_{IO}(z_O, z_I)$ denote the probability of an employer-to-employer transition from z_I to the outside sector, conditional on current search s and on the potential outside-sector draw being z_O. This probability is

$$p_{IO}(z_O, z_I) = \lambda(s)(1 - \phi_e)A_{IO}(z_O, z_I), \qquad \lambda(s) = \lambda_0 + \lambda_1 s, \tag{F.61}$$

where $1 - \phi_e$ is the probability that a contact is with the outside sector. It follows that

$$A_{IO}(z_O, z_I) = \frac{p_{IO}(z_O, z_I)}{\lambda(s)(1 - \phi_e)}. \tag{F.62}$$

Substituting into equation (F.60) yields

$$\mathbb{E}\left[V_O(z_O) \mid e, s\right] = V_I^R(z_I) + \sigma_O \mathbb{E}\left[\ell\left(\frac{p_{IO}(z_O, z_I)}{\lambda(s)(1 - \phi_e)}\right) \middle| z_I\right]. \tag{F.63}$$

The scale parameter σ_O determines how strongly acceptance responds to the value of the incumbent job. In particular,

$$\frac{\partial \ell\left[A_{IO}(z_O, z_I)\right]}{\partial V_I^R(z_I)} = -\frac{1}{\sigma_O}. \tag{F.64}$$

Let y denote the firm type, or rank, of the incumbent inside-sector firm. Holding education, search status, and the remaining components of x_I fixed, random assignment of outside offers implies

$$\frac{\partial}{\partial y}\mathbb{E}\left[\ell\left[A_{IO}(z_O, z_I)\right] \mid z_I\right] = -\frac{1}{\sigma_O}\frac{\partial V_I^R(z_I)}{\partial y}. \tag{F.65}$$

Holding the incumbent value gradient fixed, a larger value of σ_O generates a flatter relationship between expected offer-level log odds and the rank of the incumbent firm.

To connect this argument to observables, let

$$p(z_I, s) = \mathbb{P}\left[s_t = s \mid z_I\right]$$

denote the probability of choosing current search action s, and define the average contact probability

$$\bar{\lambda}(z_I) = \sum_{s \in \{0,1\}} p(z_I, s)\lambda(s) = \lambda_0 + \lambda_1 p(z_I, 1). \tag{F.66}$$

An outside-sector offer consists of $(e, \hat{q})$, where $\hat{q} \sim F_q$. Hence, $F_O(\hat{q} \mid e) = F_q(\hat{q})$. The unconditional

probability of an inside-to-outside transition from state z_I is

$$p_{IO}(z_I) = (1 - \phi_e) \sum_{s \in \{0,1\}} p(z_I, s)\lambda(s) \int A_{IO}(z_O, z_I)\, dF_O(x_O \mid e). \tag{F.67}$$

Consequently,

$$\overline{A}_{IO}(z_I) = \frac{p_{IO}(z_I)}{(1 - \phi_e)\overline{\lambda}(z_I)} \tag{F.68}$$

is the average acceptance probability conditional on an outside-sector contact, where the average is weighted by the probability of contact under each search action.

For each education group, the outside-sector payoff shifter o_e is disciplined jointly by the average level of this normalized acceptance probability and the search technology parameters:

$$m_{0,e}^{IO} = \frac{\mathbb{E}[p_{IO}(z_I) \mid e]}{(1 - \phi_e)\mathbb{E}[\overline{\lambda}(z_I) \mid e]}. \tag{F.69}$$

An increase in o_e raises outside-sector values and therefore raises $m_{0,e}^{IO}$.

Conditional on matching this average level, σ_O is chosen to match the decline in outside-sector transitions across the inside-sector firm distribution. For a firm-rank bin centered at y, define

$$\overline{A}_{IO,e}(y) = \frac{\mathbb{E}[p_{IO}(z_I) \mid e, y]}{(1 - \phi_e)\mathbb{E}[\overline{\lambda}(z_I) \mid e, y]}. \tag{F.70}$$

The preceding log-odds representation shows why the scale σ_O governs the responsiveness of outside-sector acceptance to the value of the incumbent inside-sector job. Acceptance conditional on receiving an outside-sector offer is not observed directly, however. I therefore do not match the normalized acceptance probability itself.

Instead, estimation uses the quarterly destination moments. The four education-specific average shares θ_e^{IO} primarily discipline the education-specific outside-sector payoff shifters o_e. The common pooled rank coefficient β_{IO}, summarized by $m_1^{IO} = \beta_{IO}/2$, primarily disciplines the common mobility-shock scale σ_O. A larger σ_O makes the outside-sector destination share less responsive to the rank of the incumbent firm and therefore moves m_1^{IO} toward zero.

F.8 Separation Probability in the Outside Sector

Let $L_{it} \in \{I, O, U\}$ denote the worker's labor-market state. Consider the moment

$$\theta_{OUI} = \Pr\left(L_{i,t-2} = O \mid L_{i,t-1} = U,\, L_{it} = I\right), \tag{F.71}$$

which measures the share of hires from unemployment into the inside sector who were employed in the outside sector in the preceding observation period. By Bayes' rule,

$$\theta_{OUI} = \frac{\Pr(L_{i,t-1} = U \mid L_{i,t-2} = O)\Pr(L_{it} = I \mid L_{i,t-1} = U, L_{i,t-2} = O)\Pr(L_{i,t-2} = O)}{\Pr(L_{i,t-1} = U)\Pr(L_{it} = I \mid L_{i,t-1} = U)}. \tag{F.72}$$

If the job-finding probability of an unemployed worker is independent of her previous sector, then

$$\Pr(L_{it} = I \mid L_{i,t-1} = U, L_{i,t-2} = O) = \Pr(L_{it} = I \mid L_{i,t-1} = U),$$

and hence

$$\theta_{OUI} = \frac{\Pr(L_{i,t-1} = U \mid L_{i,t-2} = O)\Pr(L_{i,t-2} = O)}{\Pr(L_{i,t-1} = U)}. \tag{F.73}$$

Thus, the moment identifies the inflow from outside employment into unemployment relative to the unemployment stock.

In the model, an outside worker enters unemployment only if no offer is accepted before the exogenous separation is realized. Consequently,

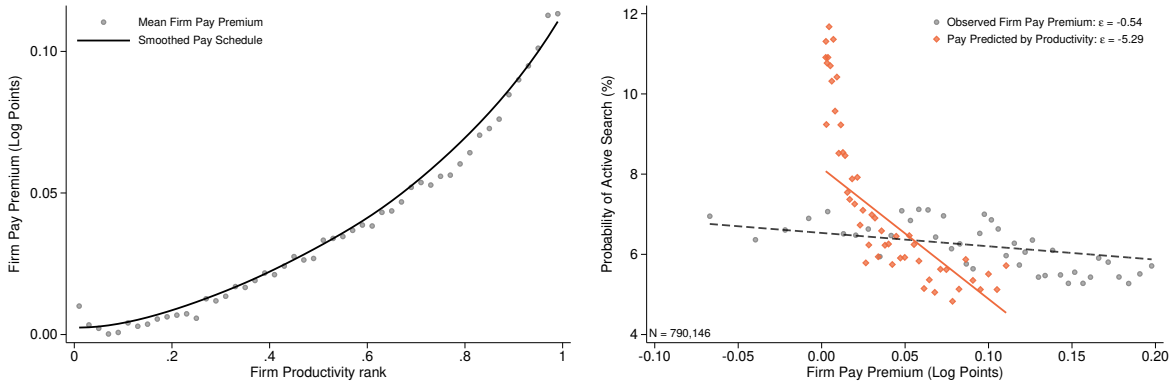
$$\Pr(U_{t+1} \mid e, q, s) = \left[1 - p_{acc}^{O}(e, q, s)\right]\delta_O. \tag{F.74}$$

Conditional on the outside-employment stock, the search and acceptance blocks, and the composition of the unemployment pool, the moment in equation (F.73) therefore disciplines the outside-sector separation probability δ_O. In estimation, we match the exact analogue of this moment in the simulated panel.

Figure A.1: Firm Pay, Productivity, and Search Effort

(a) Firm Pay Across Productivity Ranks

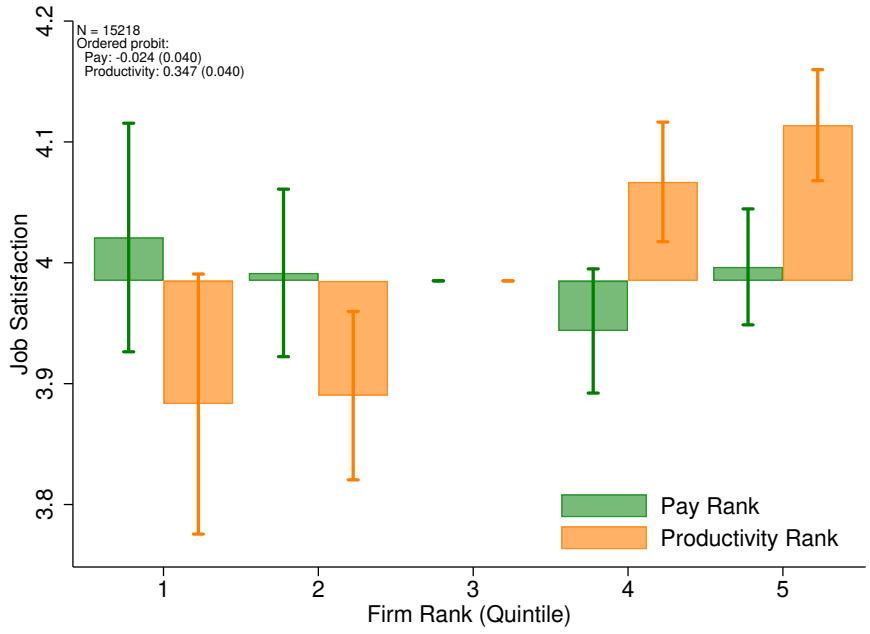
(b) Search and Observed or Predicted Firm Pay



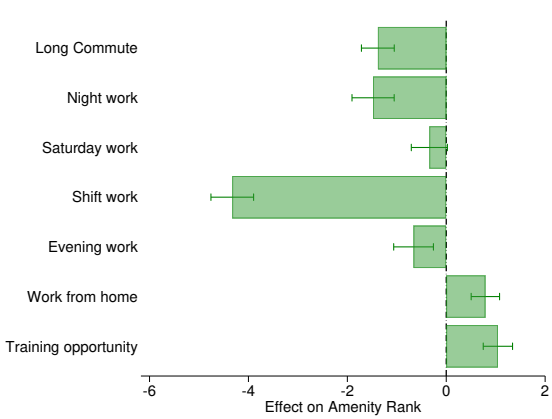
Notes: **Panel (a)** plots mean firm pay premia against firm productivity rank, together with a smoothed pay schedule. **Panel (b)** plots the incidence of active on-the-job search against observed firm pay premia and pay premia predicted by productivity. The lines summarize the corresponding search–pay gradients.

Figure A.2: Job Ladders, Job Satisfaction and Non-pecuniary Job Attributes

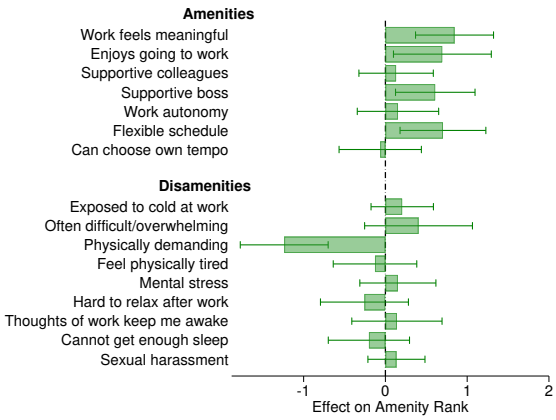
(a) Job Satisfaction



(b) Amenities (LFS)



(c) Amenities (AMU)

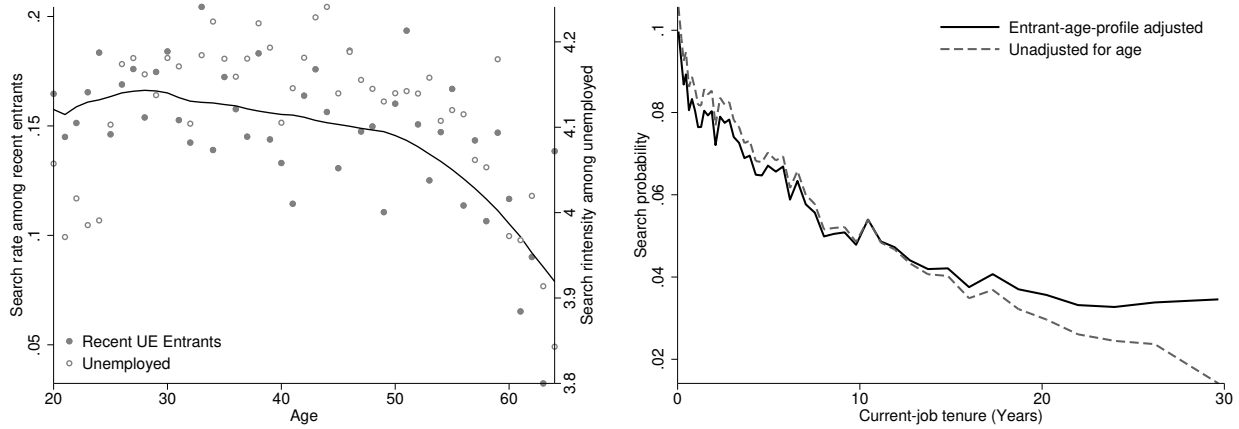


Notes: The figure explores the relationship between firm pay and non-pecuniary job attributes. **Panel a)** shows the relationship between job satisfaction of an employee and her current employer's rank in the job ladder, induced by either the firm pay premium or the value added per worker. Bars represent the coefficients from a linear projection of job satisfaction on the employer's quintile in the job ladder controlling for demographic observables and time effects. **Panel b)** and **Panel c)** show the relationship between the amenity rank of a firm, computed as the difference between productivity rank and firm pay rank, and self-reported job attributes in the LFS and AMU, respectively. The bars represent the coefficient estimates of a linear projection of the amenity rank on a set of (dis-)amenities. In **Panel b)**, amenities are coded as binary indicators. We classify a commute as a long commute if it exceeds the median commuting distance. In **Panel c)**, the coefficient estimates relate to a standard deviation in the underlying right-hand side variable. All regressions include a gender-education-specific third-order polynomial in age, gender-specific dummies for having a child below the age of five, a dummy for foreign birth. Error bars represent 95 percent confidence intervals computed under robust standard errors.

Figure A.3: Tenure and On-the-Job Search – Robustness

(a) Life-Cycle Profile

(b) Age-Corrected Tenure Profile



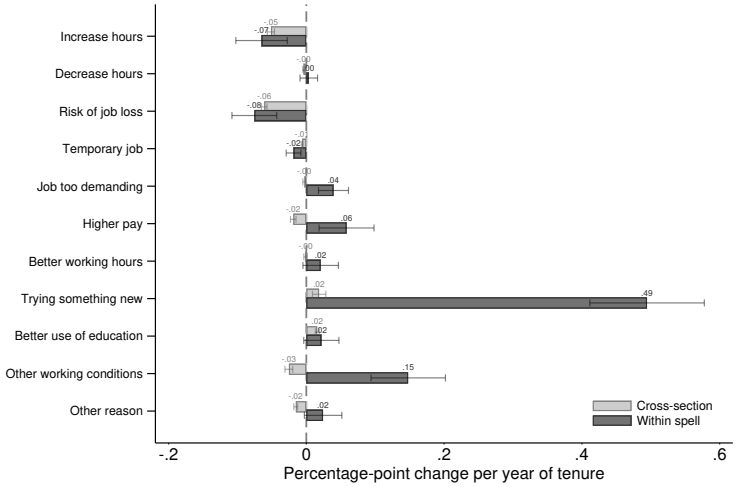
Notes: The figure provides details on the construction of the search profile by employer tenure. **Panel a)** shows the age profile of two measures of search effort. First, gray circles report age-specific means of a year-adjusted indicator for active search among workers aged 20–64 who are employed in the current LFS interview and were non-employed in the preceding observed interview. Before constructing the age profile, the search indicator is residualized with respect to calendar-year fixed effects and recentered at its sample mean. The solid black line is a locally weighted linear regression of this year-adjusted search indicator on age, estimated at the individual-observation level using a bandwidth of 0.5. Second, the hollow circles represent the average number of search methods among unemployed job seekers. This second series is shown for comparison and is not used in constructing the age adjustment. **Panel b)** demonstrates the construction of an age-adjusted tenure profile of on-the-job search. The dashed line shows the raw profile of on-the-job search with respect to tenure. The solid black line applies the entrant-age-profile correction to the same sample. Specifically, let $\widehat{m}(a)$ denote the local linear regression estimate from Panel a) and let $\overline{m}$ denote its average in the relevant employed estimation sample. Adjusted search is defined as

$$s_{it}^{adj} = s_{it} - [\widehat{m}(a_{it}) - \overline{m}] .$$

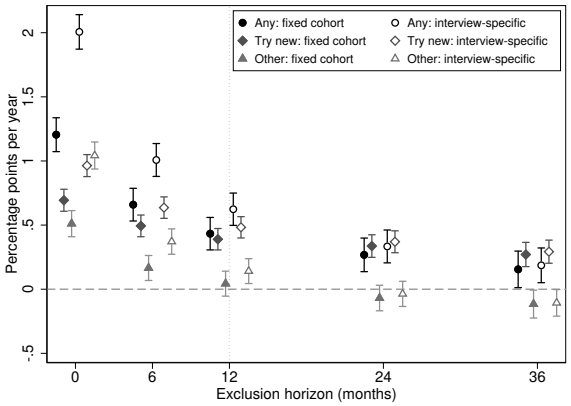
The correction therefore removes the age-specific deviation of predicted entrant search from its sample mean while preserving the overall mean search rate. The sample consists of employed job seekers in the Swedish Labor Force Survey between 2005 and 2020 who are included in the main analysis sample.

Figure A.4: Tenure and On-the-Job Search – Robustness

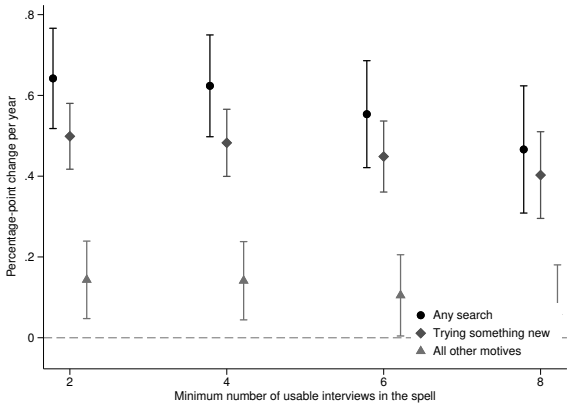
(a) Tenure and On-the-Job Search



(b) Motive Decomposition



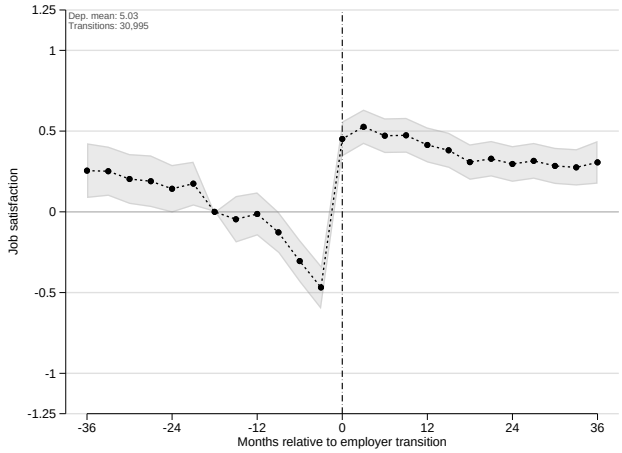
(c) Motive Decomposition



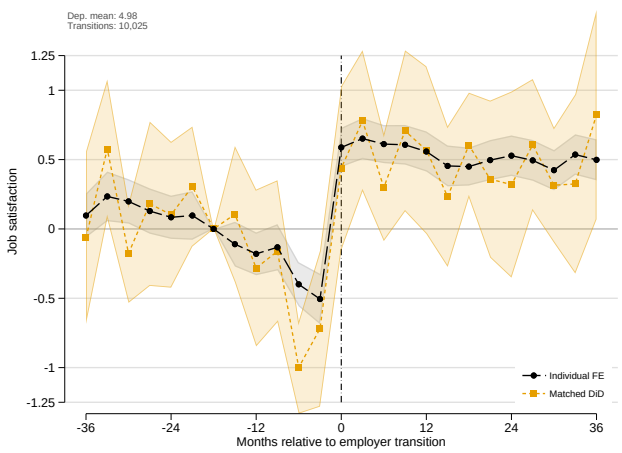
Notes: The figure provides information on the relationship between on-the-job search and employer tenure. The sample consists of observations with valid self-reported tenure in the Swedish Labor Force Survey between 2005 and 2020. **Panel a)** shows parametric estimates of the relationship between tenure and search due to different motives in cross-section and panel models. Light gray bars depict the coefficient of a linear projection of search on employer tenure in years. Dark gray bars show coefficients when panel fixed effects are included in the model. I restrict the sample to workers who are observed at least 12 months before the eventual end of their current employer spell and exhibit at least four usable interviews within the spell. **Panels b) and c)** plot coefficient estimates for any on-the-job search, search motivated by the desire to try something new, and all other motives excluding wanting to try something new under different sample restrictions. **Panel b)** varies the exclusion horizon relative to the eventual end of the current employer spell. Filled markers correspond to a fixed-cohort restriction, under which the employer spell must survive through the eighth LFS interview plus the indicated horizon. Hollow markers correspond to an interview-specific restriction, under which an observation is retained whenever it occurs at least the indicated number of months before the eventual end of the employer spell. In both cases, employer spells are required to contain at least four usable interviews. **Panel c)** varies the number of interviews required per employer spell. Standard errors are clustered at the individual level. Whiskers show 95 percent confidence intervals.

Figure A.5: Job Satisfaction Dynamics in the UK-HLS

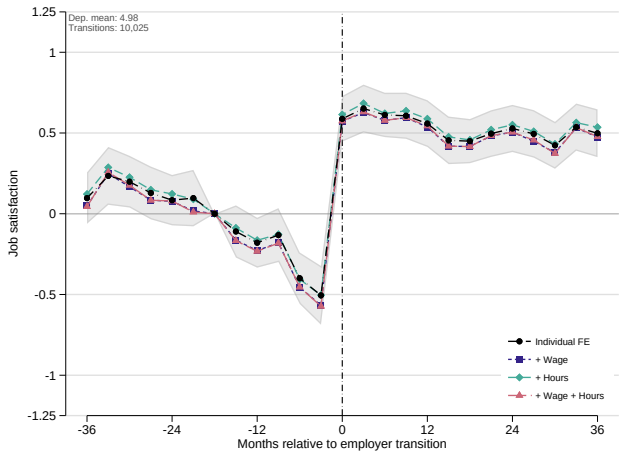
(a) Cross-Sectional Profile



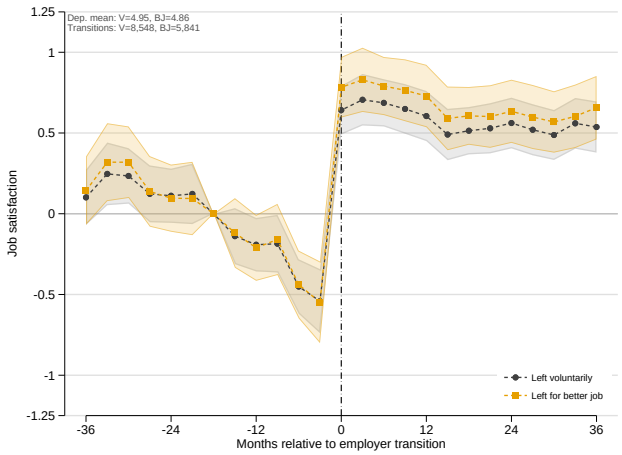
(b) Panel Models



(c) Controlling for Hours and Wages



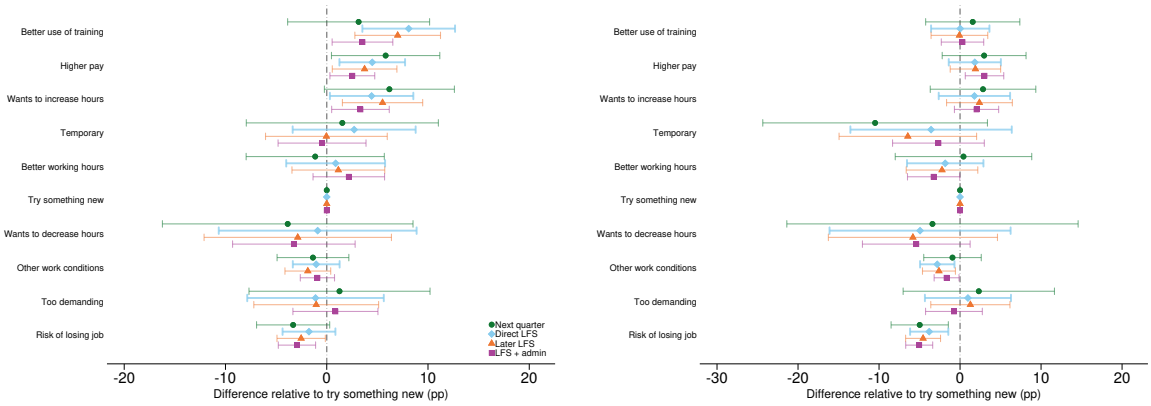
(d) Voluntary Transitions



Notes: The figure plots event-study coefficients for job satisfaction around employer transitions in the UK-HLS. Job satisfaction is measured on the original seven-point scale. Event time is measured in months relative to the first observed employer transition and grouped into quarterly bins; the x-axis reports months relative to the transition. The omitted category is the sixth quarter before the transition, $k_0 = -6$, corresponding to roughly 18 months before the move. **Panel (a)** reports the cross-sectional event-study specification with gender-by-education-by-age-by-year controls and calendar-month fixed effects; stayers are retained in the sample through a separate stayer category. **Panel (b)** compares the within-worker event profile, which includes individual fixed effects and calendar-month fixed effects, with the matched-stayer event-study design. **Panel (c)** re-estimates the within-worker specification after adding log hourly wages, log hours, or both. **Panel (d)** restricts the within-worker specification to transitions classified from retrospective separation reasons as voluntary, or to transitions where the respondent reports leaving for a better job. Shaded areas report 95 percent confidence intervals based on standard errors clustered at the individual level. Reported means and transition counts refer to the corresponding estimation samples.

Figure A.6: Direction of Mobility and Search Motives – Robustness

(a) Value-Added Rank (b) Firm Pay Rank

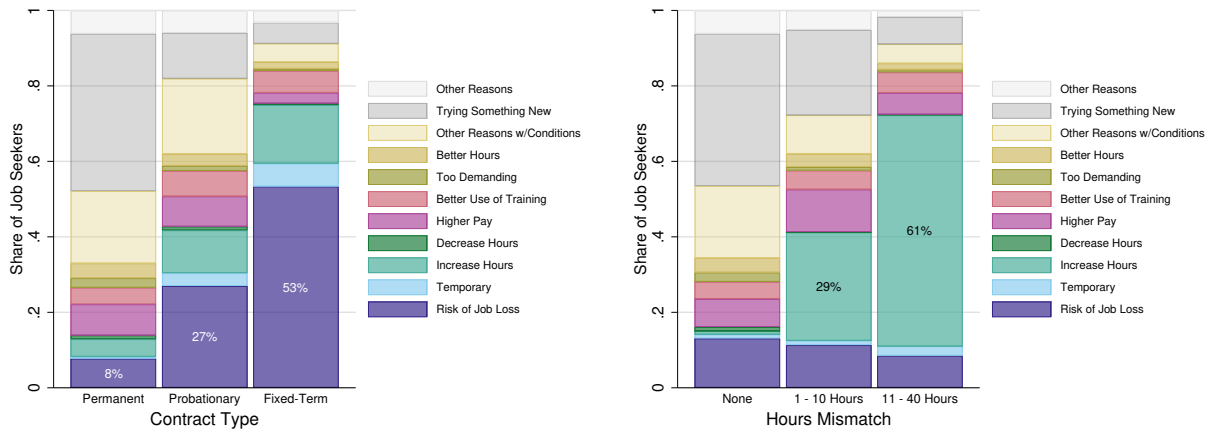


Notes: The figure relates workers' stated primary reason for on-the-job search to the change in employer rank associated with a subsequent firm move under different samples of firm moves in the data. "Next quarter" identifies workers observed at a different firm exactly three months after the search interview. "Direct LFS" uses the first different firm observed in a later LFS wave and excludes workers observed as nonemployed at an intervening interview. "Later LFS" uses the first different firm observed in a later LFS wave regardless of intervening employment status. "LFS + admin" uses the first later LFS firm when observed and otherwise the worker's next-year administrative main employer. For subsequent employers identified from administrative data I make no assumption on whether there was an intervening nonemployment spell. Since rankings are computed for two distinct time periods, the search-origin interview determines the ranking regime, and both origin and destination firms are ranked within the same regime. **Panel a)** reports changes in value-added rank. **Panel b)** reports changes in firm-pay rank within the value-added-rankable mover sample. Coefficients are expressed relative to "Try something new." Regressions include gender x age x education fixed effects and search-origin calendar-month effects. The provided sample weights are used. Standard errors are clustered at the individual level.

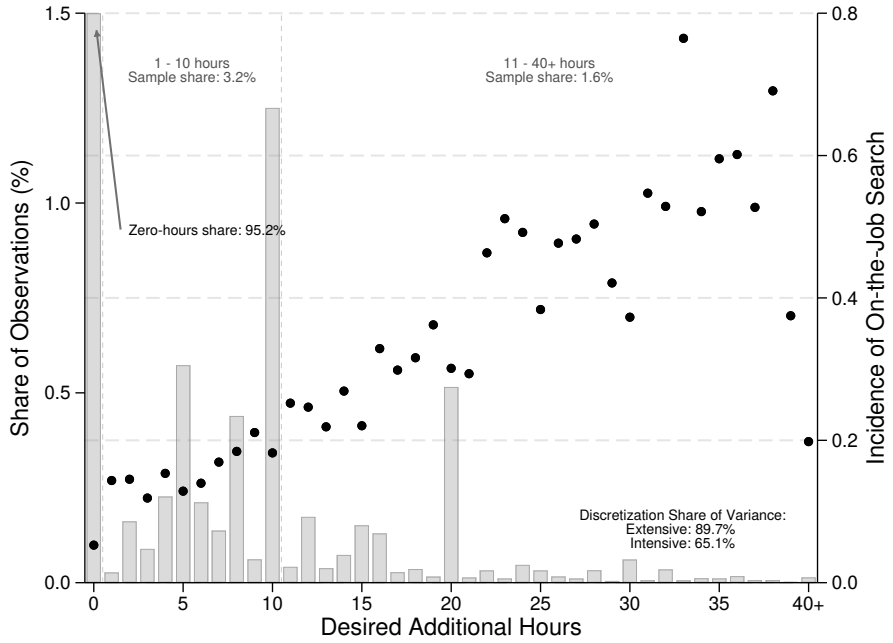
Figure A.7: Motive Decomposition by Contract Type and Hours Mismatch

(a) Contract Type

(b) Hours Mismatch



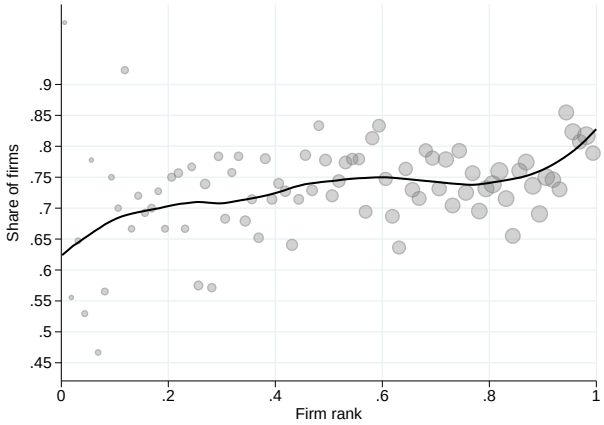
(c) Hours Mismatch and Active Search



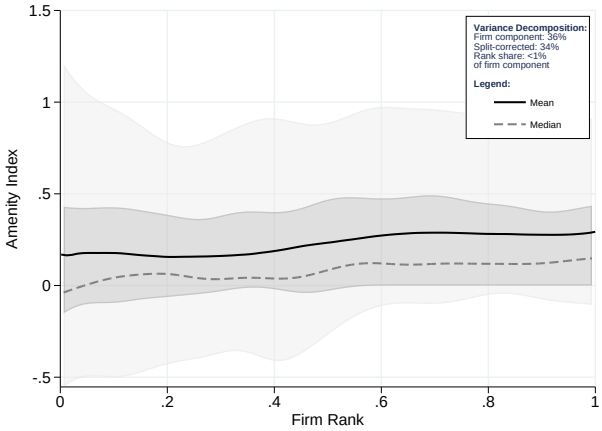
Notes: The figure shows the relationship between on-the-job search, contract type and hours mismatch. **Panel a)** displays the distribution of primary motives for search on-the-job by contract type. **Panel b)** presents the distribution of motives by hours mismatch. Hours mismatch is defined as a respondent stating that they would like to work more than their current working hours. The sample consists of employees who report having searched for another job in the past four weeks and state a reason for their job search. **Panel c)** shows the distribution of hours mismatch and its relationship with the incidence of on-the-job search. The text at the bottom right reports the share of hours mismatch that can be explained by the three groups: zero mismatch, mismatch between 1 and 10, and mismatch between 11 and 40 hours, unconditionally or conditional on reporting non-zero hours mismatch.

Figure A.8: Amenities in Vacancy Postings

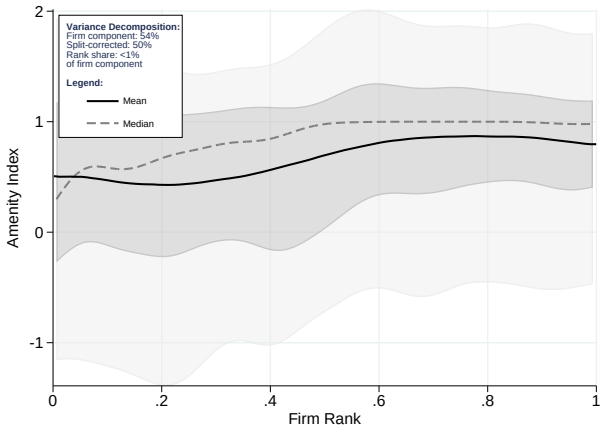
(a) Amenity Mentions in Vacancy Postings



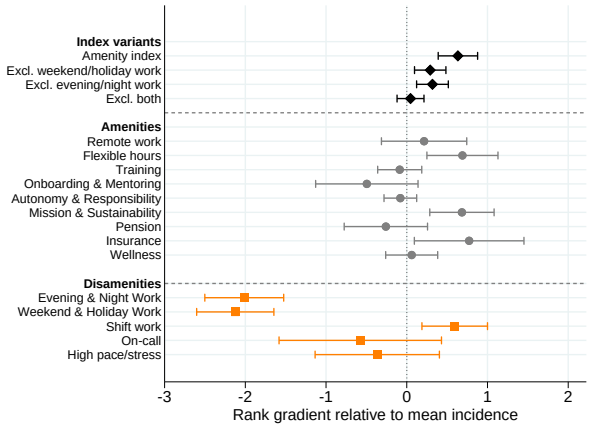
(b) Amenities Across Firms (Unconditional)



(c) Amenities Across Firms (Intensive Margin)

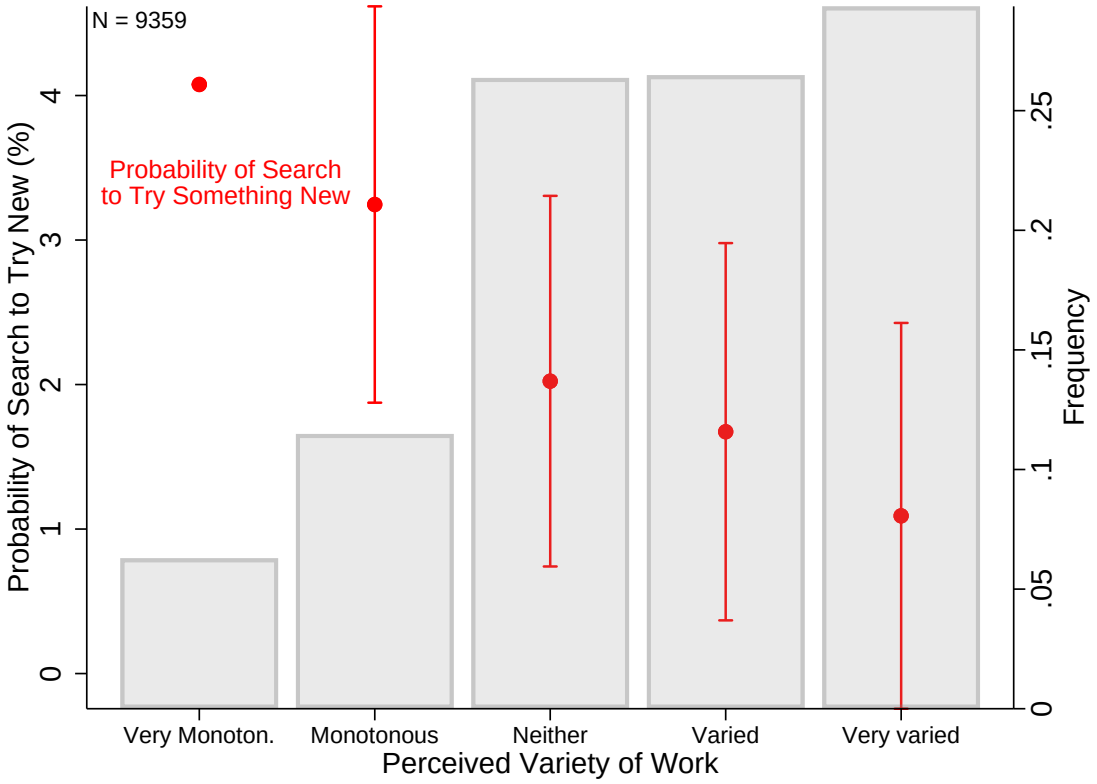


(d) Disaggregated Rank Gradients



Notes: The figure shows the relationship between firm rank and amenities in vacancy postings. The sample consists of job vacancies posted to the Public Employment Service between 2006 and 2025 by firms that can be matched to their balance sheets. Firm rank refers to the firm's rank in the national distribution of value added per employee and is normalized to lie in the unit interval. **Panel a)** shows the share of firms mentioning at least one amenity in their postings across the firm-rank distribution. **Panel b)** shows the unconditional amenity index by firm rank, assigning zero values to firms with no amenity mention. **Panel c)** shows the conditional amenity index among firms with at least one amenity mention. In Panels b) and c), solid lines report smoothed firm-level means and dashed lines report smoothed medians. Shaded areas show the smoothed P10-P90 and P25-P75 ranges across firms. The box in Panel b) reports a variance decomposition of the unconditional amenity index into firm-level variation and the component explained by firm rank. **Panel d)** reports rank gradients for selected amenity and disamenity components, normalized by each component's mean incidence. Points show coefficient estimates from firm-level regressions of each component on firm rank; horizontal bars report 95 percent confidence intervals. Gray denotes amenities and orange denotes disamenities.

Figure A.9: Love of Variety

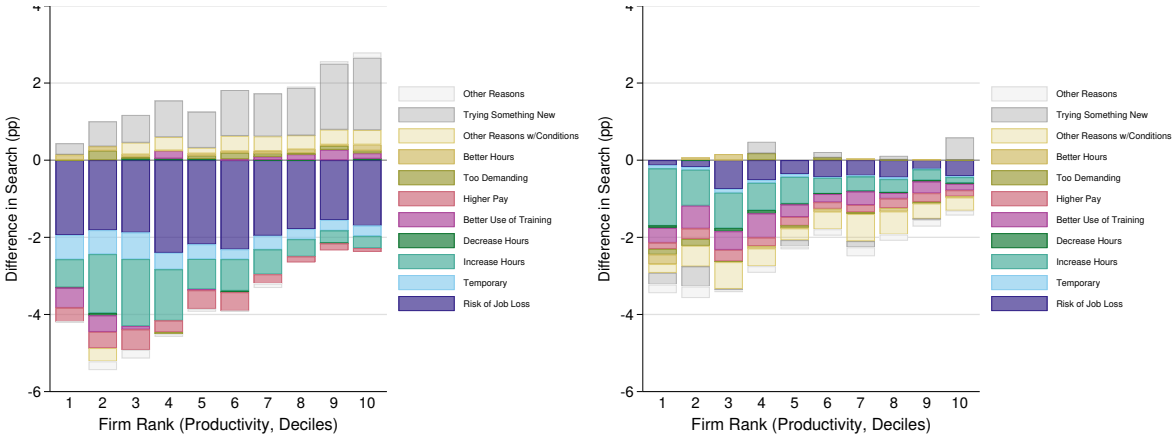


Notes: The figure shows the relationship between the incidence of search to try something new, and the perceived variety of their current work as elicited in the Swedish Work Environment Survey (AMU). Respondents are asked to rank their current job in terms of monotony or variety on a five point scale. Red dots show the coefficient of a regression of search to try something new on the five point scale, controlling for poaching rank quantile fixed effects, occupation fixed effects and a set of education dummies (interactions of 3-digit education, gender, year, and age). Red whiskers show 95 percent confidence intervals. Grey bars depict the relative frequency of responses to the perceived variety question in the overall survey population.

Figure A.10: Tenure Differences in Search by Motive

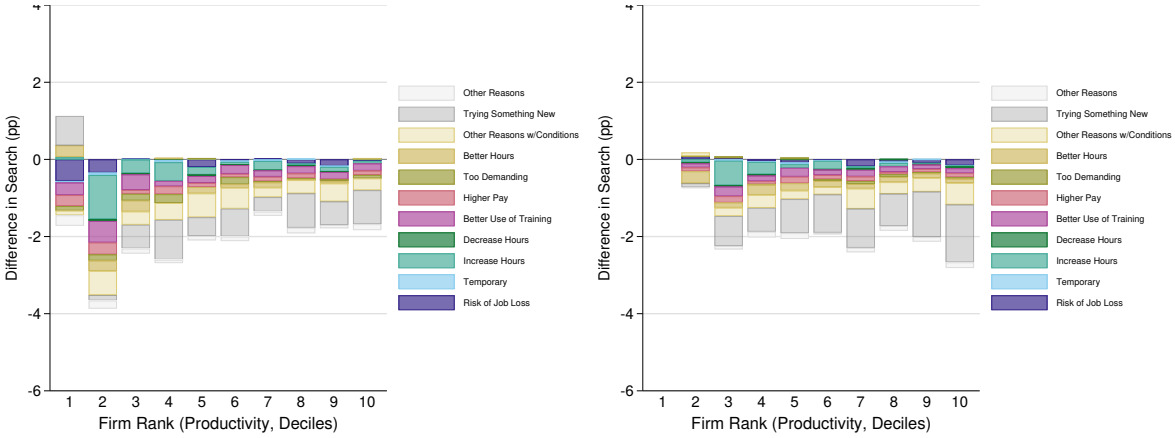
(a) 1 to 5 Years versus Less Than 1 Year

(b) 5 to 10 Years versus 1 to 5 Years



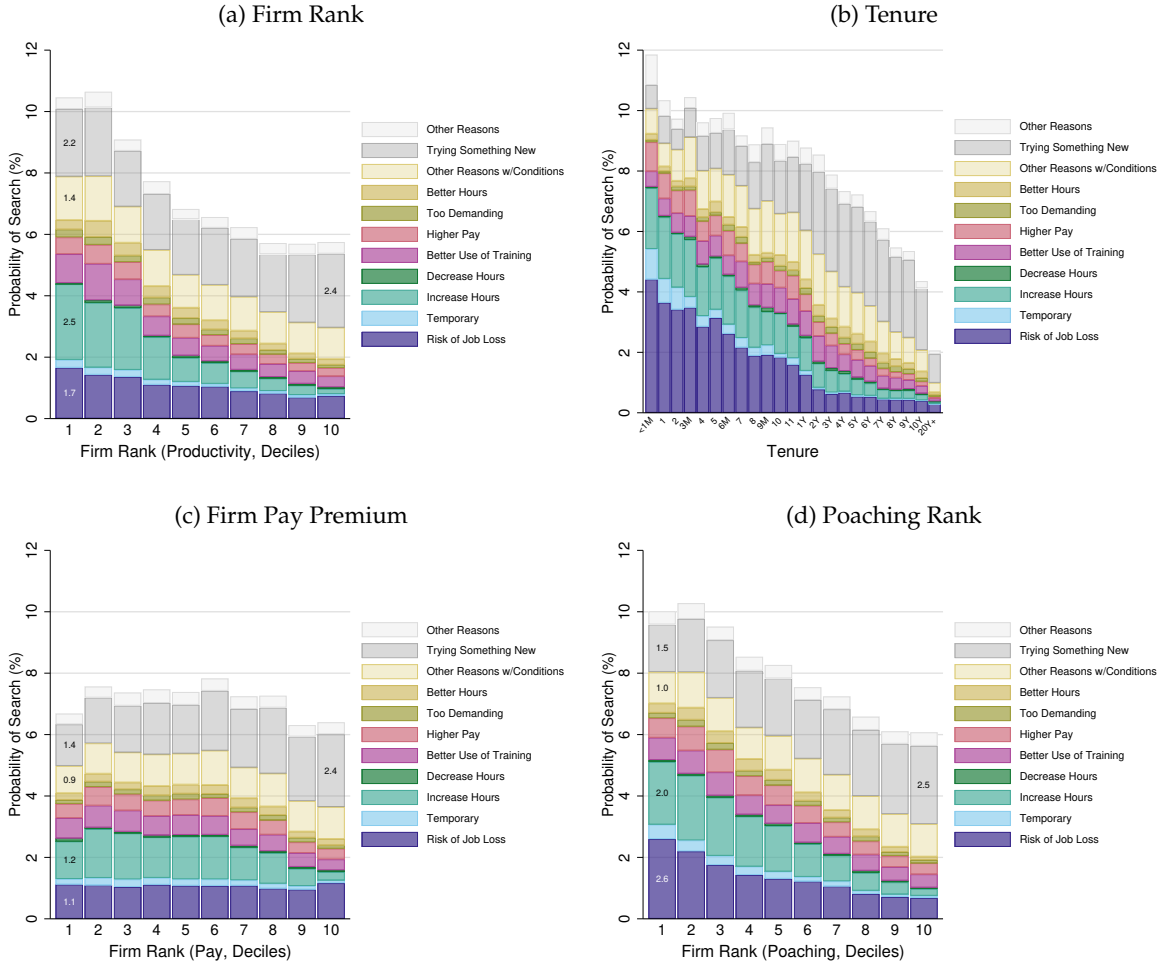
(c) 10 to 20 Years versus 5 to 10 Years

(d) More Than 20 Years versus 10 to 20 Years



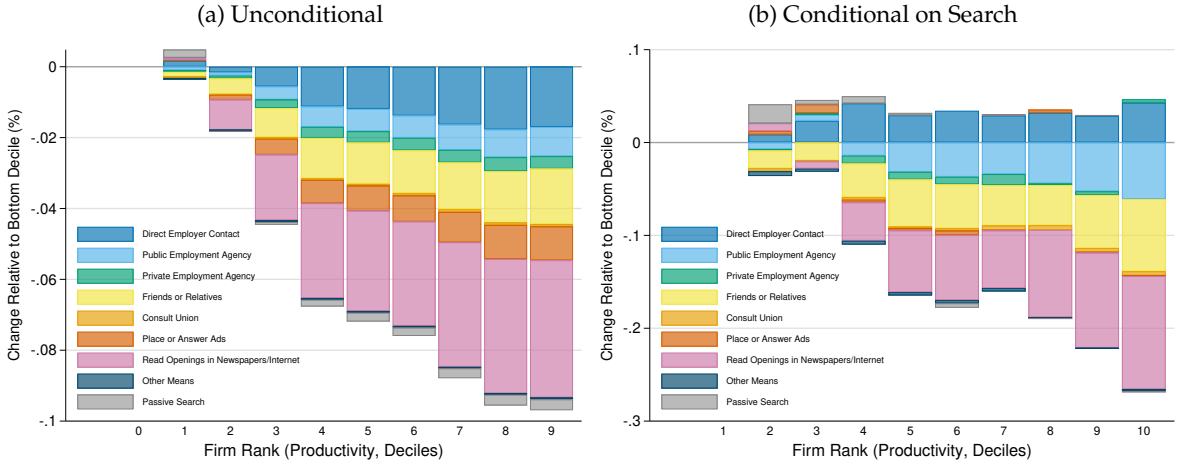
Notes: The figure shows the difference in search by motive between workers of different tenure at their current employer across the distribution of firms. Each panel computes the difference between two adjacent tenure groups. **Panel a)** shows the difference between 1 to 5 years of tenure compared to less than 1 year of tenure. **Panel b)** shows the difference between 5 to 10 years of tenure compared to 1 to 5 years of tenure. **Panel c)** shows the difference between 10 to 20 years of tenure compared to 5 to 10 years of tenure. **Panel d)** shows the difference between more than 20 years of tenure compared to 10 to 20 years of tenure.

Figure A.11: Search Incidence by Motive Across Firm Rank and Tenure



Notes: The figure displays the incidence of on-the-job search distinguished by primary motives for on-the-job search across different measures of job quality. **Panel a)** shows the incidence of search across the ranking of firms induced by value added per employee. **Panel b)** shows the incidence of search across the tenure at the current employer. **Panel c)** shows the incidence of search across the ranking of firms induced by firm pay premia. **Paneldc)** shows the incidence of search across the ranking of firms induced by poaching shares following Bagger and Lentz (2019).

Figure A.12: Search Methods Along the Job Ladder

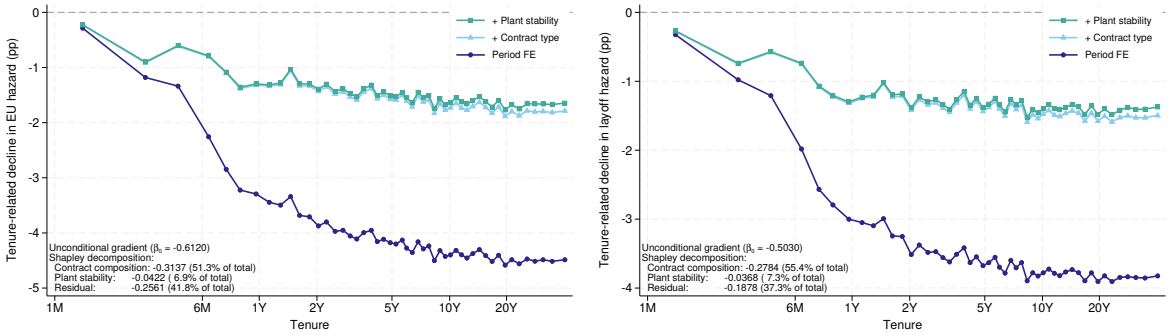


Notes: The figure shows how the use of alternative search methods varies across the productivity ranking of the worker's current employer. **Panel (a)** reports changes in the incidence of each search method in the full sample of employed workers relative to workers at firms in the bottom decile of the productivity distribution. **Panel (b)** reports the corresponding changes conditional on engaging in on-the-job search. All estimates control for demographic characteristics, family structure, and calendar-month fixed effects.

Figure A.13: Unemployment Risk by Tenure

(a) Separations into Unemployment

(b) Layoffs

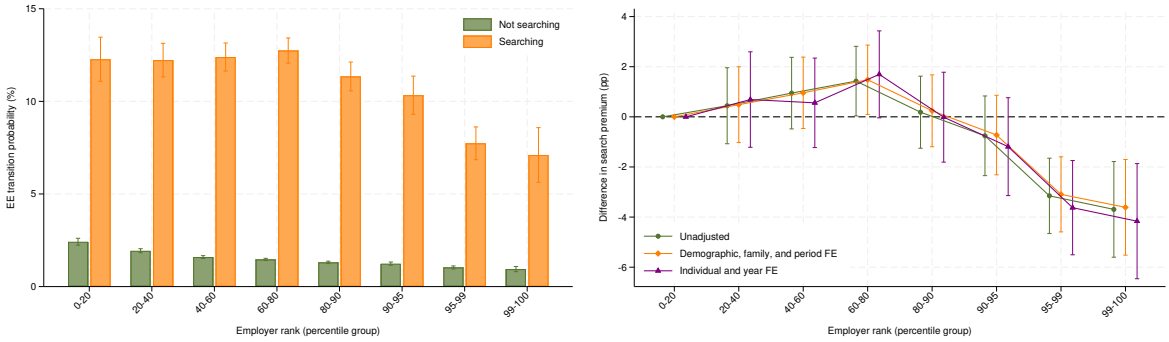


Notes: The figure shows quarterly transition rates into unemployment by tenure. In **Panel a)**, transitions encompass all flows into unemployment, including voluntary quits. In contrast, **Panel b)** only considers layoffs.

Figure A.14: Search Yields by Firm Rank and Tenure

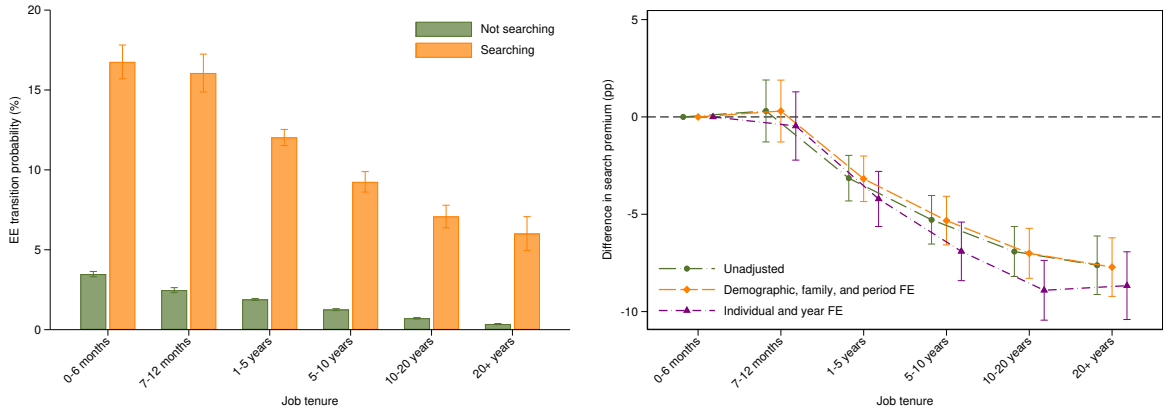
(a) Transition Probabilities by Firm Rank

(b) Search-Premia by Firm Rank



(c) Transition Probabilities by Tenure

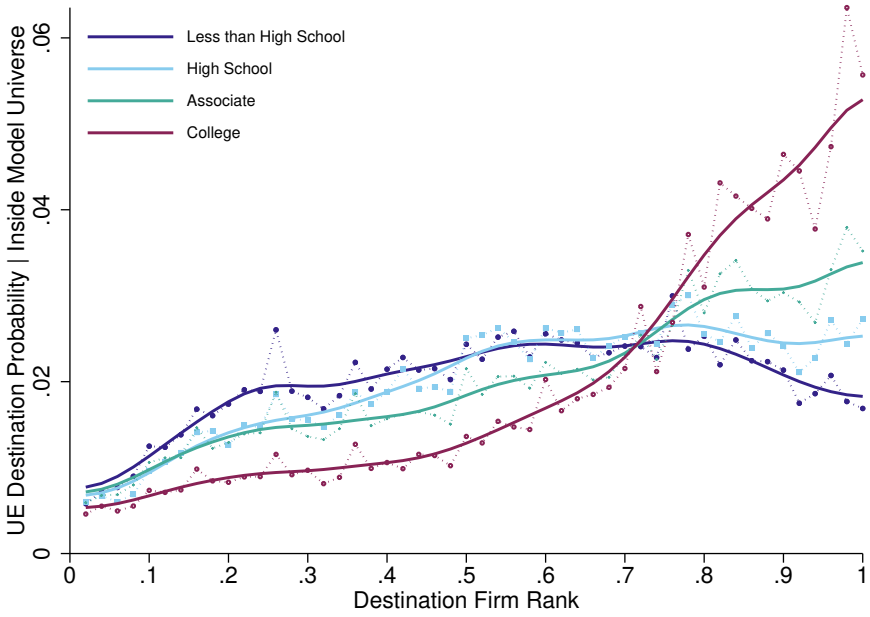
(d) Search-Premia by Tenure



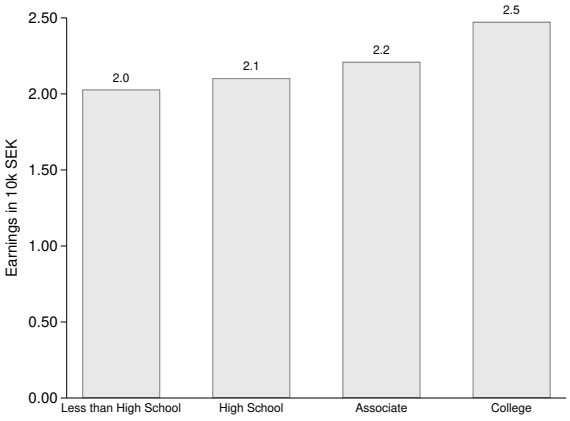
Notes: The figure shows relationship between active search and quarterly employer-employer transition rates across firm rank and tenure. **Panel (a)** presents quarterly employer-employer transition rates by search status across firms ranked by value added per worker. **Panel (b)** shows the estimated search by firm rank in alternative models. **Panel (c)** presents quarterly employer-employer transition rates by search status across tenure. **Panel (d)** shows the estimated search premium by tenure in alternative models. Whiskers represent 95 percent confidence intervals.

Figure A.15: Firm Destinations and Earnings by Education

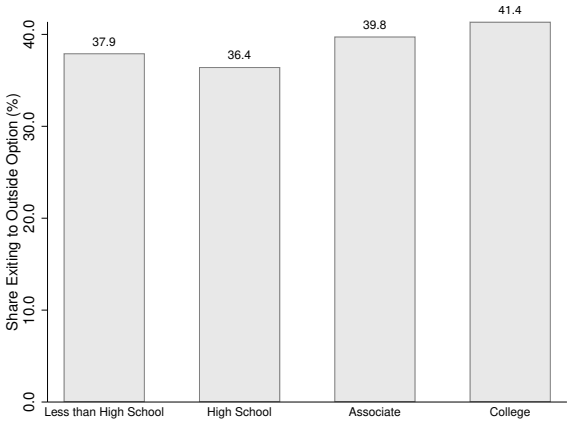
(a) Destination Firm Rank Following Unemployment



(b) Earnings by Education



(c) Outside Sector Shares Following Unemployment



Notes: **Panel (a)** shows the distribution of destination firm ranks following unemployment, conditional on the destination being inside the model universe, separately by education. **Panel (b)** reports earnings by education in units of SEK 10,000. **Panel (c)** reports the share exiting to the outside option by education.

Table A.1: Employer assignment rules in the linked LFS–RAMS sample

Rule	Assignment source	Observations (%)
1	Unique plant active in LFS reference month	1,661,107 (72.3)
2	Active plant matching LFS current-job start	123,077 (5.4)
3	Active plant matching one-digit industry	14,960 (0.7)
4	Unique active firm; earnings criterion	4 (0.0)
8	Reference/start-year plant overlap	148,518 (6.5)
9	LFS-token set fill-in	49,743 (2.2)
5	Single plant in reference year	10,738 (0.5)
6	Single substantive plant in reference year	120,223 (5.2)
7	Single plant in LFS current-job start year	8,172 (0.4)
10	Dominant annual earnings plant	60,906 (2.7)
11	Previous-year dominant plant and long LFS tenure	8,920 (0.4)
12	Spell-fill: unique source	16,858 (0.7)
13	Spell-fill: modal source	1,588 (0.1)
14	Spell-fill: same-year forward fill	2,428 (0.1)
15	LFS-token sandwich correction	876 (0.0)
0	No employer match	69,201 (3.0)
	Total	2,297,319 (100.0)

Notes: The table presents the number and share of employed LFS person-reference-month observations assigned by each employer-linking rule. Rules are ordered according to the matching hierarchy. Percentages are computed relative to all employed LFS observations with non-missing person identifiers and reference dates. Rule 0 denotes observations for which no administrative employer could be identified. The LFS workplace token is used only to track continuity within the survey and is not interpreted as an administrative establishment identifier.

Table A.2: Work Conditions and Motives for On-the-Job Search

	(1) Too Demanding	(2) Better Hours	(3) Other Reasons r/Conditions	(4) Higher Pay	(5) Try Sth. New
Work Stress and Demands					
Mentally Stressful	0.642	0.407	0.020	0.398	0.065
	(0.413)	(0.362)	(0.129)	(0.233)	(0.090)
Physically Demanding	0.616	-1.613	-0.552	-0.062	-0.106
	(0.620)	(0.693)	(0.248)	(0.376)	(0.157)
Tired After Work	-0.185	0.316	-0.054	0.070	0.003
	(0.293)	(0.270)	(0.101)	(0.174)	(0.071)
Hours Arrangements					
Work at Night	1.505	1.641	-0.022	0.602	-0.723
	(1.117)	(1.065)	(0.530)	(0.931)	(0.426)
Shift Work	-0.935	0.604	0.169	-1.387	-0.033
	(1.108)	(1.017)	(0.437)	(0.938)	(0.290)
Work from Home	0.897	1.032	-0.775	-0.100	-0.163
	(1.095)	(0.949)	(0.358)	(0.603)	(0.229)
Social Relations and Commuting					
No Trust in Colleagues	1.496	0.704	1.358	-0.297	0.718
	(0.856)	(0.742)	(0.287)	(0.601)	(0.213)
Supportive Boss	0.209	1.787	0.961	0.942	0.752
	(0.720)	(0.807)	(0.265)	(0.431)	(0.183)
Commuting Distance	0.132	0.190	0.386	-0.241	0.160
	(0.328)	(0.317)	(0.096)	(0.303)	(0.078)
Model Information					
Baseline Probability (%)	0.175	0.266	1.099	0.515	2.391
Number of Obs.	6,775	6,775	6,775	6,775	6,775

Notes: The table presents estimates of the relationship between three sets of working conditions and active on-the-job search motivated by five reasons. Numbers represent the coefficient estimates from a multivariate linear probability model of active search on the full set of amenities. In each Column, the outcome is an indicator that returns one if search takes place and a worker cites a specific reason as the primary motive for search. The full list of questions is provided in Appendix Section A.2. Commuting distance is in kilometers and log-transformed. Variables related to hours arrangements are binary. For example, the indicator for *Work At Night* takes on one if a worker reports regularly working at night in their main job. All other variables are measured on a fiv- point Likert scale. The sample consists of all biannual waves of the AMU between 2005 and 2020. Robust standard errors are reported in parentheses.

Table A.3: Robustness Checks for Longitudinal Tenure Models

	(1) Any search	(2) Try new	(3) Other motives	(4) N	(5) Spells
Panel A: Cross-sectional estimates					
Cross-section: no age correction	-0.143	0.015	-0.158	443,951	69,060
	(0.008)	(0.005)	(0.006)		
Cross-section: Age profile adjusted	-0.142	0.026	-0.168	443,951	69,060
	(0.008)	(0.005)	(0.006)		
Panel B: Within-spell estimates					
Within spell: no age correction	0.437	0.347	0.090	443,951	69,060
	(0.127)	(0.087)	(0.099)		
Within spell: Age profile adjusted	0.437	0.347	0.090	443,951	69,060
	(0.127)	(0.087)	(0.099)		
Panel C: Sample restrictions					
Full sample: no end-of-spell exclusion	1.641	0.789	0.852	613,157	96,730
	(0.126)	(0.083)	(0.101)		
Permanent at first interview	0.582	0.353	0.230	408,054	62,890
	(0.129)	(0.092)	(0.097)		
Panel D: Alternative estimands and functional form					
Adjacent-quarter change, annualized	0.769	0.595	0.175	350,831	69,009
	(0.098)	(0.067)	(0.077)		
Log tenure: fitted 12-month change	0.276	0.136	0.140	441,728	69,060
	(0.040)	(0.020)	(0.035)		
Panel E: Calendar-adjusted relative composition					
Try new relative to other motives		0.309		443,951	69,060
		(0.066)			
Dependent mean, baseline sample	4.387	1.781	2.606		

Notes: The table shows the relationship between on-the-job search and employer tenure. **Panel a)** shows cross-sectional estimates with and without age correction. The age correction uses the smoothed age profile of on-the-job search among workers who entered employment from unemployment. **Panel b)** replicates this exercise for the baseline panel model consisting of workers who are observed at least 12 months before the eventual end of their current employer spell and exhibit at least four usable interviews within the spell. **Panel c)** shows results under different sample restrictions. The first row in Panel c) removes the restriction on distance to the eventual end of the employer spell. The second row restricts the sample based on a permanent contract at the first LFS interview. **Panel d)** shows the results under alternative parametric specifications of the model. In the first row, the model is estimated in first differences using changes between adjacent quarters. The second row estimates the model with the log of tenure as independent variable and reports the average fitted change over a year. **Panel e)** reports the tenure gradient in search to try something new relative to all other motives, estimated from a stacked specification with employer-spell-by-motive and calendar-month fixed effects. Columns 1 to 3 show model results for different types of on-the-job search. In Column 1 the outcome is a binary indicator for having actively looked for another employer in the past four weeks. Columns 2 and 3 split on-the-job search into whether an individual states the desire to try something new, or other motives, as the primary motive for looking for another employer. Columns 4 and 5 report the number of observations and the number of spells, respectively. Standard errors clustered at the individual level are shown in parentheses. Observations are weighted using the LFS-provided survey weights.

Table A.4: Bargaining

	Mobility (1)	Renegotiation (2)	τ^m/τ^r (3)	Dep. Mean (4)	N (5)
Panel A. Pay					
Δ Log Hourly Wage	6.621 (3.814)	-0.120 (1.061)	-6.00	1.54	14,996
Δ Log Earnings	12.159 (3.702)	-0.130 (1.028)	-10.12	1.38	14,996
Panel B. Hours					
Δ Usual Hours / Desired Hours	57.957 (3.292)	-3.799 (1.230)	-1.65	8.48	16,417
Δ Wants More Hours	-4.167 (0.401)	0.961 (0.150)	-0.47	-4.87	16,334
Panel C. Amenities					
No Longer Works Shifts	51.662 (2.228)	2.571 (0.553)	2.17	11.97	96,482
Starts Working from Home	4.315 (0.707)	-0.293 (0.226)	-1.60	8.00	434,389
No Longer Works Evenings	39.757 (1.966)	0.676 (0.579)	6.37	21.46	124,312
No Longer Works Nights	37.243 (2.969)	1.005 (0.928)	4.01	27.81	62,706
No Longer Works Saturdays	33.368 (1.939)	-0.524 (0.592)	-6.89	24.11	115,801
Receives Training	7.633 (0.732)	0.524 (0.189)	1.58	4.61	380,550
Panel D. Occupational Mobility					
Changes 4-Digit Occupation	58.712 (1.198)	2.646 (0.180)	2.40	2.32	337,536

Notes: This table reports estimates of equation (D.9) using the Swedish Labor Force Survey. Column (1) gives the coefficient on on-the-job search followed by an employer-to-employer move. Column (2) gives the coefficient on on-the-job search without a move. The omitted category is non-searching stayers. All specifications absorb period, demographic (gender × education × age × year) and firm rank decile fixed effects, with standard errors clustered at the individual level in parentheses. Throughout, I drop respondents who search because of job-loss risk, contract expiration, or because they regard the current job as temporary, and require that no unemployment benefits are received in the interview year so that employer-to-employer transitions are measured cleanly. **Panel a)** restricts to 2019–2020, the years in which administrative earnings are available monthly. Wages are monthly earnings divided by actual hours. Actual hours are required to lie within 50 percent of usual hours, and the sample is truncated at the 5th percentile of the wage distribution. **Panel b)** restricts to respondents desiring between one and forty additional hours and drops those usually working more than one hundred hours in the main job. **Panel c)** restricts each row to respondents for whom the less desirable state obtains at t, so the outcome records leaving that state by $t+1$. All outcomes are reported in percent or percentage points, except "Δ Desired Additional Hours", which is in hours. Column (3) reports the ratio of mobility-related ex ante returns to renegotiation-related returns using the correction in (D.25). Column (4) reports the mean of the dependent variable and Column (5) the number of observations, both in the estimation sample.

Table A.5: Search Motives, Search Effort and Employer Transitions

Search Motive [Omitted = No Search]	N. of Methods (1)	Search Duration (2)	EE (t + 1) (3)	EE + EU (t + 1) (4)
Increase Hours	2.335	15.890	0.033	0.044
	(0.004)	(0.081)	(0.003)	(0.004)
Decrease Hours	1.721	8.501	0.063	0.071
	(0.015)	(0.282)	(0.012)	(0.015)
Risk of Job Loss	2.346	10.271	0.091	0.193
	(0.004)	(0.079)	(0.003)	(0.004)
Temporary Job	2.386	13.976	0.057	0.089
	(0.010)	(0.200)	(0.007)	(0.009)
Too Demanding	1.993	13.221	0.055	0.061
	(0.009)	(0.180)	(0.008)	(0.010)
Better Working Hours	1.936	9.781	0.075	0.096
	(0.004)	(0.073)	(0.003)	(0.004)
Other Reasons r/Conditions	1.713	8.006	0.058	0.070
	(0.003)	(0.053)	(0.002)	(0.003)
Higher Pay	1.925	10.260	0.056	0.064
	(0.007)	(0.144)	(0.006)	(0.008)
Better Training	2.186	12.773	0.069	0.068
	(0.006)	(0.119)	(0.005)	(0.006)
Trying Something New	1.848	10.052	0.048	0.050
	(0.005)	(0.099)	(0.004)	(0.005)
Other	1.913	9.301	0.058	0.093
	(0.006)	(0.117)	(0.005)	(0.006)
Firm Fixed Effect	✓	✓	✓	✓
Individual Fixed Effect	✓	✓	✓	✓
Dependent Mean	0.164	97.290	0.074	0.122
R2	0.788	0.395	0.450	0.472
Number of Observations	1,258,210	1,258,210	471,594	471,594

Notes: The table reports estimates of the relationship between reasons for job search, measures of search effort and realized labor mobility. The sample consists of all job seekers in the LFS between 2005 and 2020. The independent variable is a set of dummies for each primary reason for on-the-job search. In Column 1, the dependent variable is the number of search methods employed by a job seeker, set to zero in case of no active job search. In Column 2, the dependent variable is the number of weeks that the job seeker has searched consecutively leading up to the interview. In Column 3, the dependent variable is a binary indicator that takes on the value one if an individual has transitioned between employers within the next quarter. In Column 4, the dependent variable is a binary indicator that takes on the value one if an individual has transitioned either to another employer or out of employment. Controls include individual fixed effects, firm fixed effects and fixed effects for demographic groups, defined as the interaction of education (3 digits), gender and age. Since age, individual fixed effects and year are multi-collinear, I impose the restriction that age effects are identical for ages 40 to 45.

Table A.6: Firm Pay Premia and Search – Robustness

	(1)	(2)	(3)	(4)
	Broad First Stage		At Least Six Distinct Movers	
	Full Support	Central 95%	Full Support	Central 95%
Raw AKM	-0.191	-0.369	-0.279	-0.552
	(0.042)	(0.051)	(0.052)	(0.063)
Empirical Bayes	-0.228	-0.468	-0.325	-0.671
	(0.050)	(0.059)	(0.060)	(0.072)
KSS Corrected	-0.234	-0.501	-0.317	-0.675
	(0.052)	(0.069)	(0.059)	(0.077)
Number of Observations	748,319	700,074	682,162	636,638
Number of Workers	148,147	140,063	135,165	127,426
Signal-to-Total Variance Ratio	0.816	0.737	0.880	0.818

Notes: The table shows the gradient of on-the-job search with respect to firm-level pay premia under different estimation strategies and sample restrictions. The first row presents results for a regression of on-the-job search on firm level fixed effects as estimated in Abowd et al. (1999). The second row reports results when an empirical Bayes correction is applied to the fixed effects. The third row presents results obtained using the unbiased covariance estimator developed in Kline et al. (2020). In the first column, no sample restrictions are applied beyond the standard restriction to the largest leave-one-out connected set. In the second column, we drop 2.5 percent of firms at each tail of the distribution. The third and fourth columns in addition restrict the initial estimation sample to firms that exhibit at least six movers over each eight year window.

Table A.7: Establishment-Level Search Regressions

	Firm	Plant	Observations	Workers
Panel A: AKM pay premium, levels				
Raw AKM	-0.194	-0.177		
	(0.043)	(0.039)		
Empirical Bayes	-0.232	-0.234		
	(0.050)	(0.047)		
KSS Corrected	-0.241	-0.226		
	(0.053)	(0.050)		
Signal-to-Total Variance Ratio	0.804	0.784		
Common Sample			742,236	147,077
Panel B: AKM empirical-Bayes rank				
Baseline	-0.103	-0.107	742,236	147,077
	(0.017)	(0.016)		
Central 95%	-0.126	-0.132	685,407	137,527
	(0.019)	(0.017)		
At least six distinct movers	-0.125	-0.125	649,991	129,299
	(0.017)	(0.016)		
Panel C: Empirical-Bayes poaching rank				
Baseline	-0.348	-0.307	781,381	154,723
	(0.014)	(0.013)		
Central 95%	-0.340	-0.298	604,918	125,395
	(0.017)	(0.016)		
At least six eligible hires	-0.402	-0.349	711,307	142,217
	(0.016)	(0.016)		

Notes: The table shows the gradient of search with respect to an employer's position in the job ladder depending on whether employers are identified at the firm or establishment level. The underlying model is a linear projection of on-the-job search with respect to the current employer's pay premium or her position in the job ladder. The first column shows the estimated coefficient if the model is estimated at the firm-level; the second column repeats this exercise at the establishment-level. In **Panel A**, the explanatory variable is the employer's pay premium (in log levels). The gradient is estimated using raw pay fixed effects, shrunk pay fixed effects obtained from an empirical Bayes correction, or the covariance estimator developed in Kline et al. (2020). In **Panel B**, the explanatory variable is the rank of the employer in the distribution of pay fixed effects. I report results for different sample restrictions that affect the precision of the rank estimate. In **Panel C**, the explanatory variable is the employer's poaching rank as defined in Bagger and Lentz (2019) and estimated using an empirical Bayes correction based on a Beta-Binomial distribution. The sample is the Swedish Labor Force Survey between 2005 and 2020. Standard errors are reported in parentheses.

Table A.8: Gradient of Search under Alternative Labor Market Definitions

	National (1)	Within Market (2)	Observations (3)	Workers (4)
Panel A. Firm value-added rank				
Municipality	-0.047	-0.043	786,797	155,416
	(0.002)	(0.002)		
2-digit industry	-0.047	-0.031	786,797	155,416
	(0.002)	(0.002)		
Endogenous labor market	-0.046	-0.044	740,942	145,589
	(0.002)	(0.002)		
Panel B. Firm Pay Rank				
Municipality	-0.012	-0.011	743,496	147,162
	(0.002)	(0.002)		
2-digit industry	-0.012	-0.007	743,496	147,162
	(0.002)	(0.002)		
Endogenous labor market	-0.011	-0.011	699,231	137,573
	(0.002)	(0.002)		
Panel C. Poaching Rank				
Municipality	-0.040	-0.040	729,918	145,209
	(0.002)	(0.002)		
2-digit industry	-0.040	-0.035	729,918	145,209
	(0.002)	(0.002)		
Endogenous labor market	-0.041	-0.041	686,309	135,636
	(0.002)	(0.002)		

Notes: The table shows the gradient of search with respect to an employer's position in the national distribution of firms in comparison to rankings within more granular labor market definitions. The table presents results for three different definitions of a labor market: i) a municipality, ii) 2-digit industries, and iii) a flow-based education-specific labor market following Nimczik (2017). The third approach first clusters education fields according to their mobility across municipality x industry cells into twenty worker types. Within each worker type, we then partition the network induced by flows across job cells using a stochastic block model. The table presents results from a linear projection of on-the-job search with respect to the current employer's pay premium or her position in the job ladder. The first column shows the estimated coefficient if employers are ranked within the national distribution of firms. The second column shows the estimated coefficient if employers are ranked within a sub market. **Panel a)** shows the results for rankings based on value-added. **Panel b)** presents the results for rankings based on the firm pay premia estimated following Abowd et al. (1999). **Panel c)** presents the results for rankings based on a firm's poaching share. The sample is the Swedish Labor Force Survey between 2005 and 2020. Standard errors are reported in parentheses.

Table A.9: On-the-Job Search and Subsequent Unemployment Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
		EU transition			Layoff	Quit
Panel A: Pooled search						
Active Search	0.025	0.025	0.025	0.024	0.016	0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Search by reason						
Search (voluntary)	0.015	0.015	0.015	0.015	0.006	0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Search (job at risk)	0.135	0.134	0.134	0.133	0.125	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.002)
Demo × Family × Period FE		✓	✓	✓	✓	✓
Firm-rank bin FE			✓	✓	✓	✓
Tenure FE				✓	✓	✓
Dependent Mean	0.005	0.005	0.005	0.005	0.003	0.001
Share of EU gradient in (4)					0.94	0.06
R2 (Panel A)	0.007	0.009	0.010	0.013	0.010	0.006
R2 (Panel B)	0.019	0.022	0.023	0.025	0.027	0.006
Number of Observations	607,884	607,884	607,884	607,450	607,450	607,450

Notes: The table presents estimates of the relationship between on-the-job search and subsequent transitions into unemployment. The outcome is a binary indicator that assumes the value one if an individual is employed in month t and unemployed in $t + 3$, and zero otherwise. In **Panel a)**, the independent variable is an indicator for active on-the-job search. **Panel b)** breaks up active on-the-job search into search motivated by risk of job loss or contract expiration, and other, voluntary on-the-job search, and regresses unemployment transitions on both indicators. Columns 5 and 6 replace the outcome with indicators for unemployment transitions through layoffs and quits, respectively. Classification of layoffs and quits is based on unemployed respondents' self-reported reason for separation from their most recent employer. I count an observation as a layoff if it occurred due to: i) staff reduction or downsizing of operations, ii) closure, bankruptcy, or sale of the firm, or iii) contract expiration. Quits comprise worker-initiated and personal reasons (dissatisfaction with working conditions, wanting to leave, commuting, family, health, studies, retirement, military service). Columns 2 to 6 control for age – education – gender interactions, and the presence of a young child in the household. Columns 3 to 6 control for the current employer's percentile in the firm rank. Columns 4 to 6 control in addition for tenure at the current employer in months. "Share of EU gradient in (4)" expresses the coefficient on job-loss-motivated search relative to the corresponding coefficient in Column 4. The sample consists of respondents employed on permanent contracts in the Swedish Labor Force Survey between 2005 and 2020. All regressions are weighted by survey weights. Standard errors, in parentheses, are clustered at the individual level.

Table A.10: Intensive Margin of Search

	Number of Search Methods		Search Duration (Weeks)	
	(1) All Workers	(2) Searchers	(3) All Workers	(4) Searchers
Value-Added Rank	-0.129	-0.487	-0.894	-5.283
	(0.007)	(0.034)	(0.056)	(0.562)
Dependent Mean	0.128	2.072	0.666	11.067
Observations	792,087	48,099	792,087	48,099
R^2	0.014	0.038	0.003	0.033

Notes: The table reports estimates of the relationship between a firm's rank in the job ladder and proxies for search intensity. In Columns 1 and 2, the outcome is the number of search methods used for on-the-job search in the past four weeks. The number of methods ranges from 1 to 11 among active searchers. In Columns 3 and 4 the outcome is the number of weeks an individual has been looking for another job. Columns 1 and 3 estimate the model in the entire eligible population setting the outcome for non-searchers to zero. Columns 2 and 4 restrict the estimation sample to workers engaged in active job search in the last four weeks, thereby isolating the intensive margin of on-the-job search. The model is a linear regression of the respective outcome on the current employer's rank in the distribution induced by value-added per employee. Controls include gender x age x education fixed effects, calendar-year fixed effects and gender-specific dummies for the presence of a child below the age of 5 in the household. Observations are weighted using the provided survey weights. Standard errors clustered at the individual and firm level are reported in parentheses.

Table A.11: Robustness for Motive Decomposition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Searchers			Methods		EE Yield	
	Bottom	Top	Adj.	Bottom	Top	Bottom	Top
Panel A: Firm Value-Added Rank							
Risk of Job Loss	16.0	11.8	13.4	16.5	15.7	26.8	19.5
Temporary	2.7	1.0	1.6	2.8	1.4	3.9	1.4
Increase Hours	22.6	2.4	6.3	25.9	3.1	13.6	1.4
Decrease Hours	0.3	1.0	0.9	0.3	0.9	0.4	1.2
Higher Pay	8.3	6.2	5.9	7.0	5.6	7.1	5.3
Better Use of Training	5.3	4.5	3.3	5.7	5.3	5.7	4.7
Too Demanding	2.7	1.7	1.9	2.7	1.7	2.0	1.3
Better Hours	2.6	3.2	3.8	2.4	2.9	2.5	3.1
Other Reasons w/ Conditions	13.8	17.7	17.3	13.2	18.6	16.9	21.4
Trying Something New	21.8	43.7	39.5	20.2	38.5	17.1	33.8
Other Reasons	3.9	6.7	6.1	3.2	6.4	4.0	6.9
Panel B: Firm Pay Rank							
Risk of Job Loss	13.5	15.5	16.8	15.3	20.1	22.3	24.8
Temporary	2.2	0.9	0.9	2.4	1.3	3.2	1.3
Increase Hours	15.0	2.2	5.1	17.4	2.8	9.0	1.3
Decrease Hours	1.9	1.0	0.9	1.7	0.8	2.2	1.1
Higher Pay	12.5	5.8	6.2	10.9	5.0	10.6	4.7
Better Use of Training	5.5	4.6	2.8	6.8	5.4	5.8	4.7
Too Demanding	2.4	1.8	2.2	2.8	1.9	1.7	1.3
Better Hours	3.6	3.3	4.1	2.8	3.0	3.4	3.1
Other Reasons w/ Conditions	15.9	17.7	17.5	15.7	18.3	19.3	20.8
Trying Something New	23.1	40.8	36.9	20.7	35.3	17.9	30.6
Other Reasons	4.4	6.5	6.5	3.5	6.1	4.5	6.4
Panel C: Poaching Rank							
Risk of Job Loss	21.3	9.4	10.9	23.5	12.6	33.4	15.8
Temporary	3.3	0.8	1.2	4.0	1.1	4.4	1.2
Increase Hours	16.1	1.8	4.6	17.9	2.3	9.1	1.1
Decrease Hours	0.5	0.9	0.8	0.4	0.7	0.6	1.0
Higher Pay	8.5	7.4	7.9	8.2	6.6	6.8	6.4
Better Use of Training	4.6	4.0	2.6	5.4	4.5	4.7	4.3
Too Demanding	2.7	2.1	2.2	2.5	2.1	1.9	1.5
Better Hours	4.3	1.9	2.4	3.8	1.7	3.9	1.8
Other Reasons w/ Conditions	13.3	19.2	19.3	12.6	20.1	15.4	23.7
Trying Something New	20.8	45.2	41.6	17.4	41.7	15.3	35.6
Other Reasons	4.5	7.4	6.4	4.3	6.6	4.4	7.7

Notes: The shows displays the distribution of various on-the-job search efforts by primary motives across rankings of firms. Columns (6) and (7) report the estimated employer-employer transitions, using the motive-specific transition yields estimated in A.5.

Table A.12: Acceptance Behavior in the CES

	Employed Workers	
	Pooled Countries (1)	Finland (2)
Received any offer (%)	21.98	19.80
	(0.48)	(1.71)
Offers per offer recipient	2.17	1.84
	(0.03)	(0.10)
Accepted any offer | received offer (%)	25.49	42.93
	(1.17)	(4.96)
Offer-level acceptance proxy (%)	11.77	23.44
	(0.56)	(2.93)
N. of Observations	14,240	678
Offer recipients	3,120	122

Notes: The table presents descriptive statistics on job offers and acceptance behavior in Wave 61 of the Consumer Expectations Survey 2025. The sample includes respondents employed at the time of interview. Offers refer to the preceding three months and include positions with the current employer. Standard errors in parentheses are based on 10,000 bootstrap replications, resampling respondents with replacement within each country. Estimates use the provided quarterly survey weights.

Table A.13: Predictability of contract type and hours, 2007–2020

Specification	(1) Naive R^2	(2) Leave-one-out R^2	(3) Mean (%)	(4) Postings	(5) Cells
Panel A: Fixed-term contracts					
Firm	0.498	0.443	38.60	4,594,508	186,074
Firm × municipality	0.565	0.474	38.79	4,472,986	327,062
Firm × mun. × occupation	0.711	0.577	39.20	3,745,876	585,518
Firm × mun. × occ. + year	0.714	0.580	39.20	3,745,876	585,518
Panel B: Part-time hours					
Firm	0.519	0.472	23.59	4,594,566	186,076
Firm × municipality	0.577	0.495	23.64	4,473,053	327,073
Firm × mun. × occupation	0.713	0.602	25.09	3,745,937	585,533
Firm × mun. × occ. + year	0.716	0.605	25.09	3,745,937	585,533

Notes: Non-public postings, 2007–2020. Fixed-term indicates a non-permanent contract; part-time indicates *Deltid*, with full-time and full-time/part-time offers coded zero. Naive R^2 uses full-sample fitted values; leave-one-out R^2 excludes each posting when predicting its outcome. Both use the same evaluation sample, weights and denominator. Year effects are additive and jointly estimated in the final row. Mean (%) is the outcome share. Means and R^2 are vacancy-weighted; postings and cells are unweighted counts in the evaluation sample. Firms use employer names; occupation uses legacy codes. Unidentified deletion predictions are excluded.

Table A.14: Targeted moments and model fit

Moment	Empirical	Model	Empirical Std. Err.
A. Search behavior			
Mean inside-sector search (%)	6.016	6.042	0.040
Search persistence (log-odds gap)	2.598	2.580	0.016
Search-rank slope (pp per unit rank)	−4.864	−5.156	0.287
Search at 20+ years' tenure, permanent jobs (%)	3.067	3.107	0.054
B. Job finding and active hiring			
Unemployment-to-employment rate (%)	24.582	24.513	0.167
EE rate, non-searchers (%)	1.587	1.526	0.016
EE rate, searchers (%)	12.091	12.840	0.161
Active hire share, inside to inside (%)	55.800	44.313	1.280
Active hire share, unemployed to inside (%)	70.913	70.815	0.598
C. Contracts and job loss			
Permanent EU rate, non-searchers (%)	0.342	0.341	0.009
Permanent EU rate, searchers (%)	2.784	2.787	0.099
Fixed term to permanent, same employer (%)	10.554	10.594	0.201
Probationary to unemployment (%)	6.824	6.734	0.259
Fixed term to unemployment (%)	13.601	13.452	0.234
D. Outside-sector flows			
Outside destination, education group 0 (%)	12.815	13.745	0.537
Outside destination, education group 1 (%)	14.768	16.043	0.527
Outside destination, education group 2 (%)	17.126	17.990	0.732
Outside destination, education group 3 (%)	21.423	21.435	0.642
Outside destination: rank log-odds contrast	−0.178	−0.029	0.050
Outside origin among unemployed-to-inside hires (%)	43.514	36.143	1.261

Notes: The table reports the 20 scored moments. Rates and shares are in percent, with empirical Standard errors in percentage points. The search-rank slope is in percentage points per unit of rank. Log-odds measures are unscaled. Standard errors do not include model parameter uncertainty. Transition rates are quarterly and condition on model labor-force survival. EE denotes a change of employer, its denominator does not condition on employment next quarter. Permanent jobs include latent advance-notice states. The empirical long-tenure target is age-adjusted. Active hire shares measure the incremental active-contact channel. The outside rank contrast is the fitted 75th-minus-25th percentile log-odds difference.