Job Search and Employer Market Power
Preliminary: Please Do Not Cite

Ihsaan Bassier, Jeremias Klaeui and Alan Manning

11/03/2024

Abstract

This paper provides a framework for thinking about how the job search of workers affects the market power of employers. We present a way of thinking about this which encapsulates popular existing models in which employer market power is based on either frictions in labor markets or imperfect substitutability among jobs. We show how this model can be used to compute measures of the extent of employer market power and relates them to popularly used measures of concentration ratios. We use data on the search behaviour of Swiss unemployed to investigate the number of employers being considered by job-seekers using 'clicks' on vacancies to define consideration sets.

1 Introduction

Actual or threatened worker mobility plays an important role in limiting the ability of employers to exploit their workers. But there is little focus in the job search literature on how it affects the competitiveness of labor markets though a very large literature on how the job search of the unemployed affects the duration of unemployment and the quality of the post-unemployment job. The approach taken in the paper is to analyze how the job search decisions of individual workers affects their consideration sets and how this affects the elasticity of the labor supply curve facing firms, a natural measure of employer market power.

Existing models tend to make assumptions about the consideration sets of workers. In the search model of Burdett and Mortensen (1998) (what Manning, 2020, calls modern monopsony) jobs arrive only occasionally and one at a time so that a worker has at most two employment possibilities at any time (their current job and the new possibility). Jobs are assumed to be perfect substitutes in the eyes of workers. In contrast, the model based on idiosyncracies e.g. Card et al. (2017)(what Manning, 2020, calls new classical monopsony) typically assume that workers always have a choice of the full set of employers but that jobs are imperfect substitutes.

However, there is a growing recognition of the importance of consideration sets in a number of areas of economics (e.g. see Goeree, 2008; Honka et al., 2019; Abaluck and Adams-Prassl; Dinerstein et al., 2018) The second section sets out a model of how the market power of firms is related to the size of the choice (consideration) set of workers. The third section applies this model of employer market power to a model of job search which encompasses the two existing approaches described above. Our model assumes job opportunities arrive occasionally but the consideration set may contain more than one option though not include all jobs in the market. We show how market power depends on the intensity of job search, both the extensive margin (the arrival rate of job opportunities) and the intensive margin (how many jobs they consider when they do search i.e. the size of their consideration set). We derive measures of employer market power that can be estimated using information on the search activity of jobseekers and show how they can be related to the commonly used measures of concentration ratios (e.g. Azar et al., 2020). We then apply our framework to the job search behavior of UI recipients in Switzerland where we use 'clicks' data from their use of the Swiss public employment service's 'job room' to define the extent of workers' consideration sets.

The plan of the paper is as follows. The next section outlines a model of employer choice by workers in a relatively abstract setting. The third section then considers an application of this framework to the modeling of job search. The fourth section shows how to apply this to the flow of recruits from unemployment, our empirical application. The fifth section describes our data. The sixth section uses this data to estimate measures of employer market power, investigating sensitivity to different assumptions and comparing to traditional concentration indices. Finally, we consider implications for whether job search is too little or too narrow to sustain competition in the labor market.

2 Worker Choice and Employer Market Power

2.1 Utility

Assume that the utility of individual i from working for firm f is given by:

$$v_{if} = \beta log W_f + \eta_{if} = \beta w_f + \eta_{if} \tag{1}$$

where W_f is the wage assumed to be posted by employer f (common to all workers)[1] and η_{if} is an idiosyncratic component. Assume the wage and idiosyncratic component are permanent characteristics so that jobs that offer higher utility now will always do. As is usual in discrete choice models, one can think of β as a measure of the extent of heterogeneity in the idiosyncratic component across firms; a higher β can be interpreted as lower heterogeneity in η. Assume η is independently identically distributed[2] across firms on some (possibly infinite) interval $[\eta_{min}, \eta_{max}]$, with a continuous log-concave density function $g(\eta)$ which implies the distribution function $G(\eta)$ is also log-concave (Bagnoli and Bergstrom, 2005). Log-concavity is often used to derive results in search models (e.g.Burdett, 1981; Manning, 2003). The most popular functional forms used for the distribution of the idiosyncratic component, e.g. extreme value, satisfy the log-concavity condition. If a worker has a choice of a set of firms $\mathcal{F}$ of firms (which we will refer to as the consideration set) the distribution function of the maximum utility, v, can be written as:

$$H(v;\mathcal{F}) = \Pi_{j\epsilon\mathcal{F}} G(v - \beta w_j) \tag{2}$$

[1]The 'wage' could also be interpreted more generally to be any form of permanent vertical differentiation across firms as in Lamadon et al., 2022

[2]Though all results go through if the distributions are not identical, it just adds a lot of notation.

Given the assumed log-concavity of $G(\eta)$, $H(v;\mathcal{F})$ will also be log-concave. Also assume there is always the option of being unemployed that offers utility:

$$v_{iu} = \beta log B + \eta_{iu} = \beta b + \eta_{iu} \tag{3}$$

where b is the log value of unemployment (in wage-equivalents). Assume η_u has a log-concave distribution function $G_u(\eta_u)$ independent of the idiosyncratic components in job utility. If the maximum utility from the available set of firms is v, the probability of being in employment is $G_u(v - \beta b)$.

2.2 The Supply of Labor to an Individual Firm

Consider workers who have a draw of idiosyncratic utility η from firm f so they have utility $\beta w_f + \eta$. These workers will acept this firm's offer if they have no better offer and and the offer is better than unemployment which happens with probability $H(\beta w_f + \eta; \mathcal{F}\backslash\{f\}) G_u(\beta(w_f - b) + \eta)$ where the notation $\mathcal{F}\backslash\{f\}$ denotes the set $\mathcal{F}$ excluding this firm f. As η has density $g(\eta)$ the probability of a worker choosing firm f from the set $\mathcal{F}$ can be written as:

$$n(w_f;\mathcal{F}) = \int_{\eta_{min}}^{\eta_{max}} g(\eta) H(\beta w_f + \eta; \mathcal{F}\backslash\{f\}) G_u(\beta(w_f - b) + \eta) d\eta \tag{4}$$

As long as β is finite (however large) labor supply will be a continuous function of the wage. The case where jobs are perfect substitutes is, however, different. In this case the labor supply will be the discontinuous max function. A number of properties of $n(w_f;\mathcal{F})$ are useful for later.

Proposition 1. $n(w_f;\mathcal{F})$ is:

1. $n(w_f;\mathcal{F})$ *is* increasing in the offered wage w_f
2. The elasticity of $n(w_f;\mathcal{F})$ with respect to the wage w_f is decreasing in w_f
3. Adding an extra firm to the set $\mathcal{F}$ which is chosen with a probability that depends on w_f reduces the elasticity of $n(w_f;\mathcal{F})$ with respect to the wage w_f

Proof. See Appendix 8.1. □

Proposition 1.1 simply says that as the wage rises, workers are more likely to choose it over other firms and unemployment. Proposition 1.2 tells us that the market power of employers as measured by the wage elasticity of employment increases as the wage increases. This will have important implications later. Finally, Proposition 1.3 formalizes the notion that that the labor market for an individual firm is more competitive if workers have a choice of more employers (though only those where the probability of choosing the extra job depends on the wage offered by this one); this is very intuitive. One situation in which an extra firm does not change the competitiveness of the market is if the extra job is never chosen by the worker; adding irrelevant jobs makes no difference to the labor supply elasticity as would be expected.

2.3 Employer Market Power as the Choice Set Becomes Large

We think of a competitive labor market as one in which a worker has lots of options. But does employer market power go to zero as the number of choices goes to infinity? To address this question in the context of a symmetric equilibrium we consider the case where a worker has C options all of which pay the same wage in equilibrium (though the chosen wage has to be optimal from an individual firm perspective). To keep things simple we also assume that workers always prefer employment to unemployment so that $G_u() = 1$.

Proposition 2. *In a symmetric equilibrium where employment is always prefered to unemployment:*

1. the elasticity of labor supply to an individual firm can be written as*:*

$$\epsilon = \beta \left[C g(\eta_{max}) - \frac{g'(\eta_{max})}{g(\eta_{max})} + \int_{\eta_{min}}^{\eta_{max}} \left[\frac{g'(\eta)}{g(\eta)} \right]' G(\eta)^C \, d\eta \right] \tag{5}$$

1. The elasticity is an increasing, concave function of C if $g(\eta)$ is log-concave.

2. A necessary and sufficient condition for the elasticity to become infinite as $C \to \infty$ is that $g(\eta_{max}) > 0$

Proof. See Appendix 8.2. □

The necessary and sufficient condition for the elasticity to be finite even as the choice set becomes very large is that the density of the best possible value of the idiosyncratic component of utility is zero (Berry and Pakes, 2007, make a similar point). Intuitively, with a non-zero probability of the best draw of the idiosyncratic component the distribution of the gap between the first- and second-best values of the idiosyncratic component collapses to zero as $C \to \infty$ in which case the worker's choice simply comes down to the wage. A model with the property that $g(\eta_{max}) > 0$ is Bhaskar and To (1999) who assume that workers and firms are uniformly distributed on the edge of a circle. In this case the maximum value of the idiosyncratic component corresponds to a 'distance' of zero. But the idiosyncratic component can be bounded above and the limit of the elasticity still be finite. An example is if firms and workers lived on a uniform featureless plain so that the number of firms increases with the distance instead of being uniform; the set of firms rises with the distance from the worker's location. And if, as seems plausible, the idiosyncratic component is really the sum of lots of small individual components then one would expect that the probability of them all taking their maximum value is vanishingly small. The popular MNL model has the feature that η is unbounded above with a density which then has to go to zero. In this case the second term in (5) is 1 and the final term is $-\frac{1}{C}$ [3] leading to the familiar expression for the elasticity $\beta \left[1 - \frac{1}{C}\right]$. C can be thought of as infinite in the case where each firm is assumed infinitesimal in relation to the market (Card et al., 2017; Lamadon et al., 2022) but finite when the number of firms is assumed finite (Berger et al., 2022; Jarosch et al., 2019). The term $1/C$ is the first place where one can see a connection to traditional concetration indices as this is the value of the HHI index when firms are of equal size.

[3] because $\left[\frac{g'(\eta)}{g(\eta)}\right]' = -\frac{g}{G}$ in this case

3 Job Search

The previous section was about labor supply of workers conditional on a choice set, and job search is essentially a model for the determination of the consideration set and how it changes. This section applies the set-up of the previous section to model job search in a way that allows a wider range of possibilities than most of the literature. In the new classical monopsony tradition (e.g. Card et al., 2017), the most common assumption is that all firms are in the choice set, $\mathcal{F}$ but that the jobs are imperfect substitutes; these models are typically static but if all jobs are always available any time dimension is irrelevant because workers can optimise period by period. In contrast, search models (e.g. Burdett and Mortensen, 1998) assume the consideration set is very restricted, that there is one alternative firm in addition to the current firm (if the worker is currently employed). Often these models assume jobs are perfect substitutes ($\beta = \infty$ in our notation). Our set-up aims to encompass both traditions.

Assume that both employed and unemployed workers receive opportunities to get or change jobs at a rate λ; this means that the reservation utility level will be the utility from unemployment as accepting or refusing a job has no consequences for future job opportunities[4]. With one eye on the empirical application we refer to an opportunity to change jobs as a 'session'. Assume δ is the exogenous job destruction rate. With the assumption that the idiosycratic component is fixed, no worker would ever want to quit to unemployment even if the unemployed sometimes refuse jobs.

Also assume that when the worker has the opportunity to get or change jobs they have a choice of a set of firms C other firms chosen at random (this is the size of their consideration set). In terms of (4) this means that the set $\mathcal{F}$ has cardinality C if the worker is currently unemployed and $C + 1$ if currently employed (i.e. the worker can choose to remain at the existing firm[5]. The usual search model has $C = 1$.

3.1 The Labor Supply to a Firm

To derive the extent of employer market power we need the wage elasticity of the labor supply curve to a firm that pays a certain wage. This can be derived from (4) if we take account of the endogeneity of the set $\mathcal{F}$. A useful trick given our assumptions is the following. Whenever workers become unemployed, all previous job opportunities become void; the worker is forced to start the process of finding a good job again. Index by x the number of sessions the worker has had to take or change jobs since last becoming unemployed. Denote by $\phi(x)$ the fraction of workers at every point in time who have had x opportunities. Appendix 8.4 shows that this is given by:

$$\phi(x) = \left(\frac{\lambda}{\delta + \lambda}\right)^x \phi(0) = \left(\frac{\lambda}{\delta + \lambda}\right)^x \frac{\delta}{\delta + \lambda} \tag{6}$$

To keep things simple assume that the overall set of firms is so large that a firm is never sampled twice. Then a worker who has had x sessions will have sampled Cx jobs; denote this set by

[4] This is just to keep things simple to clarify the key ideas; one can generalize to the case where job offer arrival rates are different for the employment and unemployed

[5] One could treat the number of jobs in the consideration set as stochastic; this adds notation for little insight

$\mathcal{F}(x)$. From these jobs, the worker will take the best option (which might be unemployment) and the choice will be given by (4). The order that these jobs will have been received in does not matter; the worker will currently have the best option.

An individual firm will hire a worker who has had $x\,(>0)$ sessions if they are one of the firms being considered (this happens with probability equal to Cx/F) and if they are the best option. Using (4) this means that labor supply to a firm that pays w_f will be given by:

$$N_f\left(w_f, ..\right) = C\frac{L}{F}\sum_{x=1}^{\infty}\phi\left(x\right)xE\left[n\left(w_f;\mathcal{F}\left(x\right)\right)\right] \tag{7}$$

where the expectation is over the set of other job offers that the worker has received in x sessions. We assume that the distribution of other job offers is independent of what this firm pays so is treated as exogenous from the perspective of the individual firm. $N_f\left(w_f, ..\right)$ is log-concave in the offered wages as it is a linear function of the log-concave functions $n\left(w_f;\mathcal{F}\right)$ (proved in Proposition 1); this has the implication that the firm as a wage elasticity of labor supply curve that is, ceteris paribus, decreasing in the own wage.

The firm will choose the wage to maximize profits $\pi\left(w_f\right) = \left(P - W_f\right)N_f\left(w_f, ..\right)$. As labor supply is log-concave, the profit function will be strictly log-concave which implies a unique choice of the wage however the distribution of wage offers is drawn. As usual, the first-order condition is:

$$\frac{W_f}{P - W_f} = \frac{\partial logN_f\left(w_f, ..\right)}{\partial w_f} \tag{8}$$

The left-hand side of (8) is increasing in the wage and the right-hand side decreasing, another way of showing the optimal wage must be unique. One implication of the uniqueness of the optimal wage is that if firms are homogeneous and the way that wage offers are drawn the same for all of them, then the equilibrium must be a single wage. This shows that the equilibrium wage dispersion result of Burdett and Mortensen (1998) is a knife-edge result deriving from the assumption that all jobs are perfect substitutes. If jobs are perfect substitutes the choice model (4) becomes a max function and labor supply discontinuous in the offered wage at any wage where there is a mass point of other wages. Intutively, if there is a mass point of wages at one point, a firm can always increase proftis by offering an infinitesimally higher wage as profit per worker hardly changes but the number of workers rises discontinuosuly. But as soon as β is finite, however high, this argument for equilibrium wage dispersion breaks down though others (based on employer heterogeneity) remain.

3.2 The determinants of employer market power

(8) says that wages will be lower the lower is the wage elasticity of labor supply to the employer. From (7) this can be written as:

$$\frac{\partial logN_f\left(w_f, ..\right)}{\partial w_f} = \frac{\sum_{x=1}^{\infty}\phi\left(x\right)xE\left[n\left(w_f;\mathcal{F}\left(x\right)\right)\frac{\partial logn\left(w_f;\mathcal{F}(x)\right)}{\partial w_f}\right]}{\sum_{x=1}^{\infty}\phi\left(x\right)xE\left[n\left(w_f;\mathcal{F}\left(x\right)\right)\right]} \tag{9}$$

The following Proposition provides some results on how market power is affected by parameters of the model

Proposition 3. Employer market power is decreasing in:

1. λ/δ the arrival rate of job opportunities relative to the job destruction rate

2. C the number of alternatives considered at each opportunity;

Proof. See Appendix 8.3. $\square$

These results can be related to existing measures of the competitiveness of labor markets. For example, λ/δ is used as a measure of monopsony power in Burdett and Mortensen (1998). And the number of firms in the consideration set, C, affects market share in the popular MNL model (e.g. see Card et al. (2017). It is also related to the concentration measure which, in the case of identical employers is given by $1/C$. One other parameter that might be expected to reduce market power is β which measures the extent to which employers are close substitutes for each other and importance of idiosyncracy; this is the classic measure of monopsony power in the new classical literature. But there can be individual firms where an increase in β raises market power; e.g. in the MNL model if this firm is a low-wage firm, then an increase in β lowers market share which tends to off-set the direct effect. However, averaged across all firms, one would expect that an increase in β reduces employer market power.

One feature of (9) is that the total arrival rate of job offers λC is not sufficient to measure the market power of employers. To see this, consider a special case in which we have an MNL structure and employment is always preferred to unemployment. In this case, in a symmetric equilibrium (9) will become:

$$\frac{\partial log N_f\left(w_f,..\right)}{\partial w_f}=\beta\left[1-\frac{\delta}{\lambda C}\sum_{x=1}^{\infty}\left(\frac{\lambda}{\delta+\lambda}\right)^x\frac{1}{x}\right] \tag{10}$$

For a given level of λC (10) shows that the market power of employers will be increasing in λ. An implication is that labor markets will be more competitive if workers are considering many offers simultaneously rather fewer offers arriving more frequently. The intutition for this can understood by thinknig about a static model in which workers have a one-shot choice over a set of employers. If all workers have a choice of 5 employers the extent of competition will be given by the level associated with this choice set. Now imagine replacing this with a situation in which half the workers have no offers and half have 10 so the expected number of offers is the same. The workers with no offers are in a bad situation but they contribute nothing to the level of competition. That will be determined by those who do have offers and because all of these now have 10 offers the market will be more competitive.

4 The Elasticity of the Flow of Recruits from Unemployment

The discussion so far has been about the wage elasticity of the labor supply to the firm as a whole. But our empirical application is about the flow of recruits from unemployment and the elasticity formulae for market power will be different for this (or any other) group because their labor supply elasticity may differ. The next section presents an application of a 'bottom up' approach to measuring employer market power which builds firm-level labor supply elasticities from the individual level. We then use this approach to estimate the wage elasticity of an individual unemployed worker to firms in their consideration set and then aggregate these individual-level elasticities to estimate elasticities to the vacancy level.

4.1 A Bottom-Up Approach to Measuring labor Supply Elasticities

We normally think of the labor supply elasticity at firm-level because this will determine the mark-down of wages from marginal products. This section shows how one can construct a 'bottom-up' version from labor supply elasticities at individual level. This offers the advantage that individual-level rather than firm-level elasticities may sometimes (as in this paper) be easier to estimate. Suppose that the probability of individual i from working for firm f is given by $\theta_{if}\left(W_f,.\right)$ i.e. depends on the offered wage, W_f,but also on other stuff that we do not need to specify. From this function we can derive the elasticity of labor supply of individual i to firm f as:

$$\varepsilon_{if}\left(W_f,.\right)=\frac{\partial log\theta_{if}\left(W_f,.\right)}{\partial logW_f} \tag{11}$$

If each firm could individualize the wage (i.e. act as a discriminating monopsonist separately for every worker) $\varepsilon_{if}\left(W_f,.\right)$ would be relevant for the mark-down that worker i would have; this would be relevant if the firm individualized wages. Where wages cannot be individualized a weighted average of the individual-level elasticities will be relevant. For example, in the simplest case where the firm cannot wage discriminate (i.e. pays the same wage to all its workers) the supply of labor to firm f is $\sum_j \theta_{jf}\left(W_f,.\right)$ so that the elasticity of labor supply to firm f can be written as:

$$\varepsilon_{f}\left(W_f,.\right)=\frac{\sum_j \theta_{jf}\left(W_f,.\right)\varepsilon_{jf}\left(W_f,.\right)}{\sum_j \theta_{jf}\left(W_f,.\right)} \tag{12}$$

i.e. a weighted average of the individual elasticities with the weights given by the probability of the worker working for the firm[6]. (12) shows how measures of market power at the individual level can be used to inform market power at the firm level. We can also derive the average elasticity experienced by individual i; this will be given by:

$$\sum_f \theta_{if}\left(W_f,.\right)\varepsilon_{f}\left(W_f,.\right)=\sum_{i,j} \theta_{if}\left(W_f,.\right)\theta_{jf}\left(W_f,.\right)\varepsilon_{jf}\left(W_f,.\right) \tag{13}$$

Note that the competitiveness of the labor market facing an individual depends on the elasticity of labor supply not primarily of themselves but the elasticity of those workers with whom they tend to work. A worker with very inelastic labor supply will be in a competitive labor market if they tend to work with very mobile workers while a very mobile worker will find they are highly

[6] 12 seems undefined if $\theta_{if}\left(W_f,.\right)=0$ but this does not matter as a worker that has no probability of working at a firm is irrelevant to its market of power. An alternative way of writing the firm-level elasticity is $\varepsilon_{f}\left(W_f,.\right)=\frac{\sum_j \frac{\partial \theta_{jf}\left(W_f,.\right)}{\partial logW_f}}{\sum_j \theta_{jf}\left(W_f,.\right)}$ which makes this clear.

exploited if they tend to work with very immobile workers. One implication of (13) is that workers may have a weak incentive to maintain the competitiveness of labor markets through their job search as the benefits of increased labor market competition largely flow to others; the final section discusses the possible implications of this. In this paper we use the bottom-up approach applied to the unemployed. The next section considers the elasticity of their labor supply.

4.2 The wage elasticity of the labor supply of the unemployed

Consider an individual unemployed worker, i; they will have a particular, fixed value of unemployment given by $\beta b + \eta_{ui}$. The probability of this worker choosing firm f from the set $\mathcal{F}$ can, by analogy to (4), be written as:

$$\theta_i\left(w_f;\mathcal{F}\right) = \int_{\beta\left(w_f-b\right)+\eta_{ui}}^{\eta_{max}} g\left(\eta\right) H\left(\beta w_f + \eta; \mathcal{F}\backslash\left\{f\right\}\right) d\eta \tag{14}$$

For a given assumption about the distribution of the idiosyncratic shocks this formula can then be used to derive the labor supply elasticity. We will use a common, simple functional form, namely that the choice between the different options and unemployment has a MNL form in which case (14) can be written as:

$$\theta_i\left(w_f;\mathcal{F}\right) = \frac{e^{\beta w_f}}{e^{\beta b+\eta_{ui}} + \sum_{j\epsilon\mathcal{F}_i} e^{\beta w_j}} = \frac{\sum_{j\epsilon\mathcal{F}_i} e^{\beta w_j}}{e^{\beta b+\eta_{ui}} + \sum_{j\epsilon\mathcal{F}_i} e^{\beta w_j}} \frac{e^{\beta w_f}}{\sum_{j\epsilon\mathcal{F}_i} e^{\beta w_j}} = \rho_i\left(w_f;\mathcal{F}\right) s_i\left(w_f;\mathcal{F}\right) \tag{15}$$

The last two terms write the probability of choosing an individual firm as the probability of choosing any firm (i.e. leaving unemployment) times the probability of choosing this firm conditional on leaving unemployment. Differentiating (15), the wage elasticity can then be written as:

$$\epsilon_{if} = \frac{\partial log\theta_i\left(w_f;\mathcal{F}\right)}{\partial w_f} = \frac{\partial log\rho_i\left(w_f;\mathcal{F}\right)}{\partial w_f} + \frac{\partial log s_i\left(w_f;\mathcal{F}\right)}{\partial w_f} = \beta\left[\left(1-\rho_i\right)s_i + 1 - s_i\left(w_f;\mathcal{F}\right)\right] \tag{16}$$

In what follows, we, for the moment, assume that workers always choose employment over unemployment. Relaxing this is to come. The the elasticity at the firm level will be given by:

$$\varepsilon_f = \beta\frac{\sum_i \theta_i\left(w_f;\mathcal{F}\right)\left[1-\theta_i\left(w_f;\mathcal{F}\right)\right]}{\sum_i \theta_i\left(w_f;\mathcal{F}\right)} = \beta\left[1 - \frac{\sum_i \theta_i\left(w_f;\mathcal{F}\right)^2}{\sum_i \theta_i\left(w_f;\mathcal{F}\right)}\right] \tag{17}$$

where the summation is over individuals who have firm f in their consideration set. In what follows we provide estimates of the second term in square brackets which is relevant to employer market power. We do not estimate β though that is important for a full assessment of employer market power (and may be the more important factor). The second term has affinities to HHI indices because it involves sums of squared shares. For this reason we refer to them as concentration indices. But the way in which the employment shares enter our concentration indices is a bit different. A standard HHI measure uses the shares of the firm in employment or vacancies. In contrast, ours starts from the individual level and then averages over the individuals who have this firm in their choice set. We now turn to our empirical implementation.

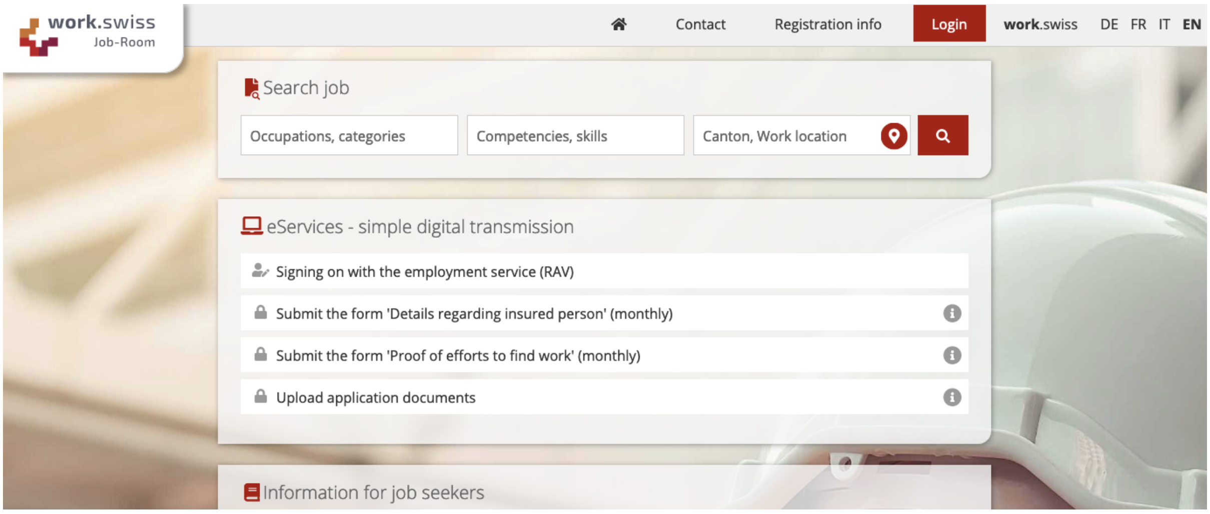

Figure 1: Screenshot from `https://job-room.ch/home/jobseeker`. Screenshot taken 10-02-2023.

5 Data

Our main data source is the activities of unemployed job-searchers using the 'job room' of the Swiss public employment service (`https://job-room.ch/home/jobseeker`), available in German, French, Italian, and, conveniently for many of us, English. The vacancies in the job room are both directly posted there and scraped from other locations; the claim is that it has the universe of job vacancies in Switzerland though, in practice it is unlikely to have 100% coverage. Even if all vacancies are in the job room, they will often also be posted elsewhere; later we discuss how we deal with the fact that we only observe a fraction of the job search activity of our sample.

When looking for vacancies in the job room the front screen looks like Figure 1, asking for occupation/category, competencies/skills and canton/work location. After filling some or all of these categories the jobseeker is presented with a range of available vacancies. For example, after a search of occupation "Office managers" in "Zurich", the jobseeker sees a set of vacancies like those shown in Figure 2 . To find out more about these vacancies (and possibly to apply for them through the portal) the jobseeker needs to 'click' on them and it is these clicks that are the basic data we use as a measure of jobs that are being considered by the jobseeker. There are few existing studies using click data - though probably more coming. Faberman and Kudlyak, 2019 investigate how search intensity using clicks varies with search duration, Adrjan and Lydon, 2019 show that clicks correlate with other measures of labor market tightness and Hensvik et al., 2021 investigate how seach behavior changed during the pandemic.

Our use of clicks data to define the consideration set deserves some discussion. One can think of it as representing some degree of interest between simple awareness of a job vacancy and an application (which have been studied elsewhere e.g. Banfi and Villena-Roldán, 2019 Azar et al., 2022a). All of these measures are of some interest but none are perfect. 'Awareness' has the obvious problem that it is hard to measure but awareness of a job that a searcher has no interest in or no chance of getting does nothing to make the labor market more competitive (as Proposition 1.3 showed). A click suggests some minimal level of interest in the job. At

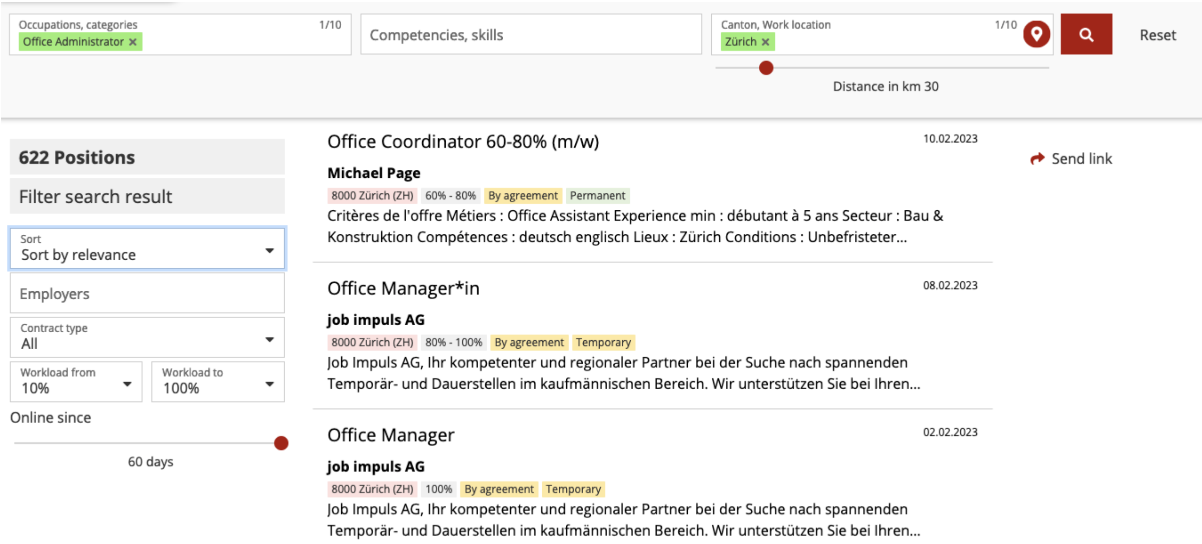

Figure 2: Screenshot of the result list when searching for "Office managers" in Zurich on the job room (`https://job-room.ch/home/jobseeker`). Screenshot taken 10-02-2023.

the other end, an application represents more serious interest but perhaps goes too far in the other direction; one might think that labor markets are more competitive if there are more jobs of interest to a searcher even if they only apply for a few of them ex post. For example, if information on the vacancy is sufficient to determine the optimal job, and all applications led to a job offer, one would only ever see one job application (to the desired job) but this would be misleading about the extent of labor market competition.

While the job room can be used by anyone, our sample is of unemployed jobseekers who are claiming UI. We have all the clicks from registered unemployed in the window 06-06-2020 - 30-06-2021. This is during the pandemic in which unemployment in Switzerland rose from 4% to 5.6% and our findings may apply only to that period. A sample of the registered unemployed has the advantage that we observe some characteristics about them, including their previous jobs and the future job (if any). This is also a group of jobseekers who are encouraged to use the job room although they are not required to. A condition of UI receipt is evidence of job search and using the job room is an easy way to provide evidence of search so we would expect many of the unemployed to use it. Nonetheless, there are other sources of information about vacancies and we do not observe this; we are only observing a sub-set of job search. Later we discuss how we deal with this issue.

318,114 unemployment spells start within the window in which we have the click data. A small proportion of individuals have more than one spell overlapping the window, such that in total the 318 114 spells correspond to 294 823 individuals. When we exclude jobseekers with incomplete education, residence, or prior earnings information, the sample is 285,033 spells. 45% have created a login for the job room, and at least one click is made in 30% of spells. We further exclude jobseekers who seem to be on temporary lay-offs, i.e. where the pre- and post-unemployment job is the same (this being a feature, for example, of seasonal work in construction (Liechti et al., 2020)). Our final sample is 81,006 unemployed job seekers with at least one click on the platform; Table 1 presents some descriptive statistics and compares the

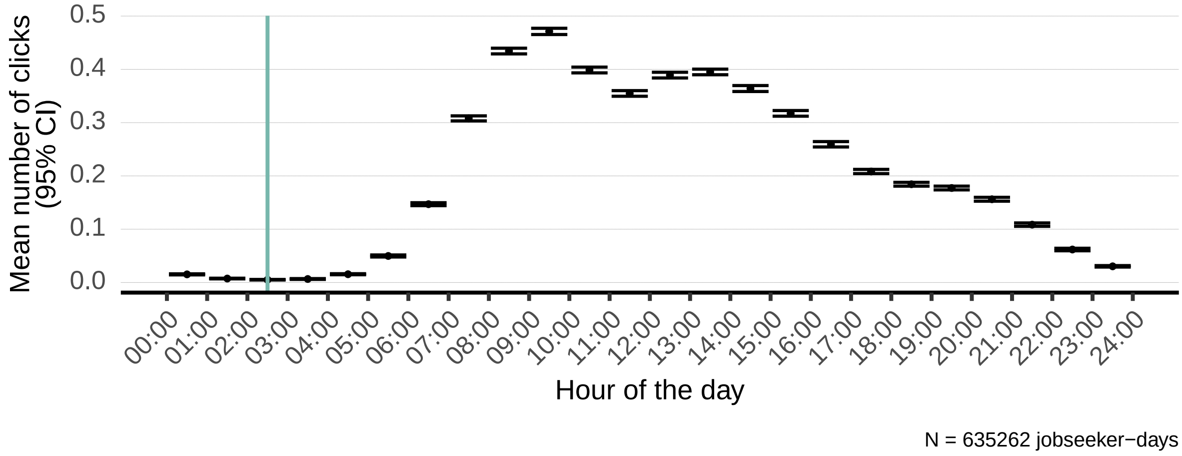

Figure 3: Number of clicks by time of the day. Averages over jobseekers.

sample to the population of registered unemployed.

	Sample (N = 81 006)			All spells (N = 285 033)			Difference	
	Mean	Min	Max	Mean	Min	Max	Difference	p-Value
Female	0.51	0.00	1.00	0.46	0.00	1.00	0.06	0
Age (at registration)	38.77	18.00	68.12	38.06	18.00	71.04	0.71	0
Primary education	0.20	0.00	1.00	0.30	0.00	1.00	-0.09	0
Secondary or vocational educ.	0.56	0.00	1.00	0.53	0.00	1.00	0.03	0
University education	0.24	0.00	1.00	0.17	0.00	1.00	0.07	0
Non-permanent resident	0.19	0.00	1.00	0.22	0.00	1.00	-0.03	0
> 3 years tenure in last job	0.66	0.00	1.00	0.63	0.00	1.00	0.03	0
Insured earnings (CHF)	4554.40	0.00	12350.00	3982.06	0.00	12350.00	572.34	0
Spell duration (months)	6.81	0.03	23.50	5.26	0.03	23.50	1.55	0

Table 1: Descriptive statistics on the characteristics of the jobseekers in our sample. The sample is compared to the characteristics of the population of registered jobseekers whose spells start within the period in which clicks on Job Room are recorded (06-06-2020 - 30-06-2021)

The main way in which our sample of unemployment spells differs from all spells is that it is better-educated and, reflecting that, has a higher level of insured earnings.

We divide the way job seekers use the job room into sessions and the number of clicks per session. We interpret a session as being an opportunity to consider a set of jobs (x in the stylized model above) and the number of clicks per session to be the size of the consideration set (C in the model above). We define a session to be a day in which there is at least one click. Assuming sessions never last more than a day and there is never more than one session per day seems reasonable due to the following. Figure 3 shows the distribution of the total number of clicks by time of day; unsurprisingly, there are very few in the middle of the night. For this reason, we assume 'days' start at 2:30am.

To justify assuming at most one session per day, define sessions on the same day as different when the interval between clicks exceeds z hours. For example, if a jobseeker has one session in the morning and another in the evening, this would show up as an interval of 6+ hours between clicks. As we vary the time interval Figure 4 shows that the average number of sessions is not much above 1 until we come to implausibly short intervals such as 15 minutes.

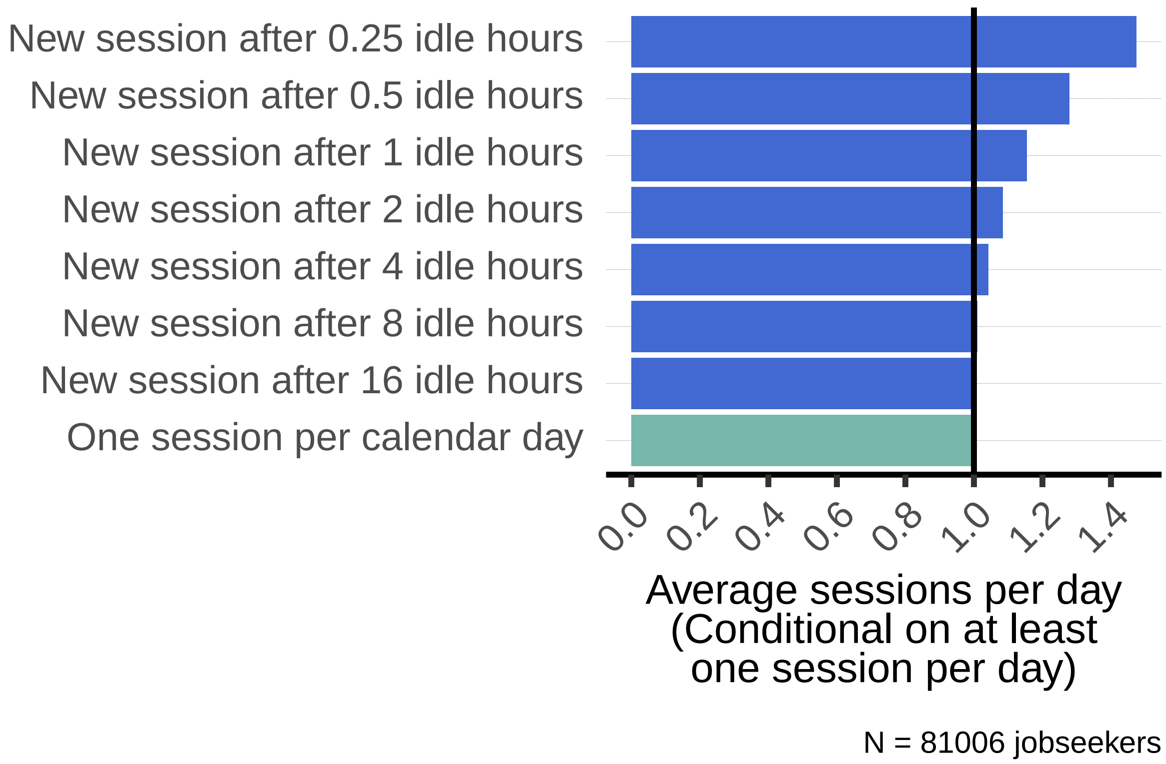

Figure 4: Number of sessions per day with different definitions of a session. Averages over jobseekers.

We disregard all clicks made before registration and after deregistration at the employment agency (those clicks account for approximately 0.4% of total clicks). If an ad is clicked twice during the same day, we consider this as one click[7]. Clicks on the same ad in two distinct sessions are counted separately. Using this definition of a session Figure 5 shows the distribution of the number of sessions per month.

The mean is 1.94 i.e. the average job seeker is using the job room every two weeks. Figure 6 shows the distribution of the number of clicks per session.

The mean is 4.9 but the long right tail means the median is 3. This is quite a low level of search activity, suggesting that observed worker consideration sets are quite small; this will have implications for our measures of employer market power. However, it should be borne in mind that we only observe part of job search. For context Krueger and Mueller (2011) report that their sample of the unemployed in New Jersey spent an average of 98 minutes a day on job search, DellaVigna et al. (2022) report 81 minutes per day.

There is, of course, systematic variation in the extent of search activity across individuals and, for the same individual, over the course of an unemployment spell. This is not our main focus of interest, so we do not discuss it in the main text. But Appendix C shows that search activity tends to fall over the course of a spell, consistent with other studies e.g. Faberman and Kudlyak, 2019 and Hensvik et al., 2021.

[7]Most of those clicks are from the same minute, suggesting that they are attributable to technical issues rather than specific search behaviour.

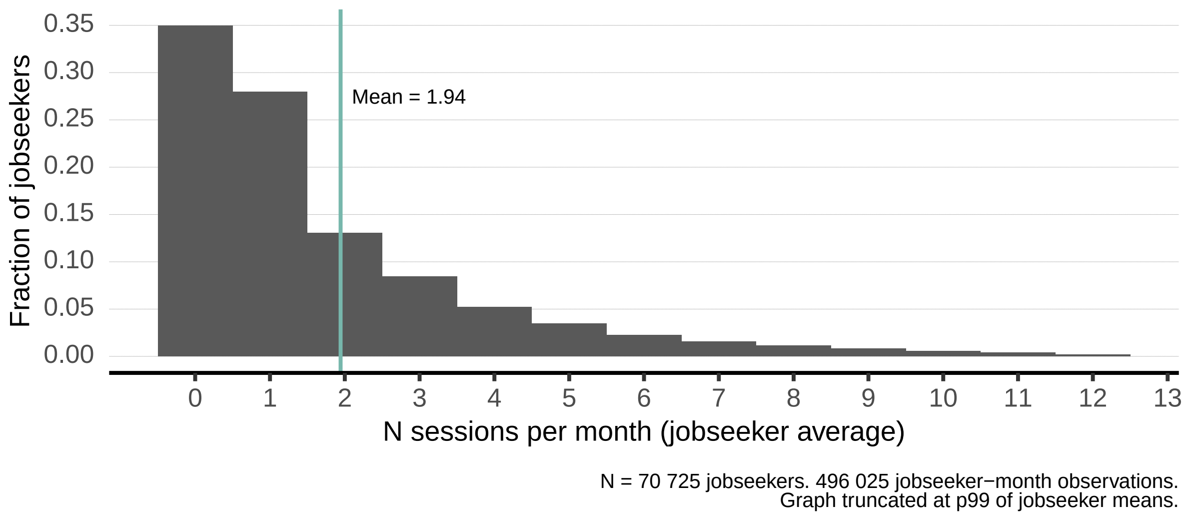

Figure 5: Distribution of the number of sessions per month. Averages over jobseekers.

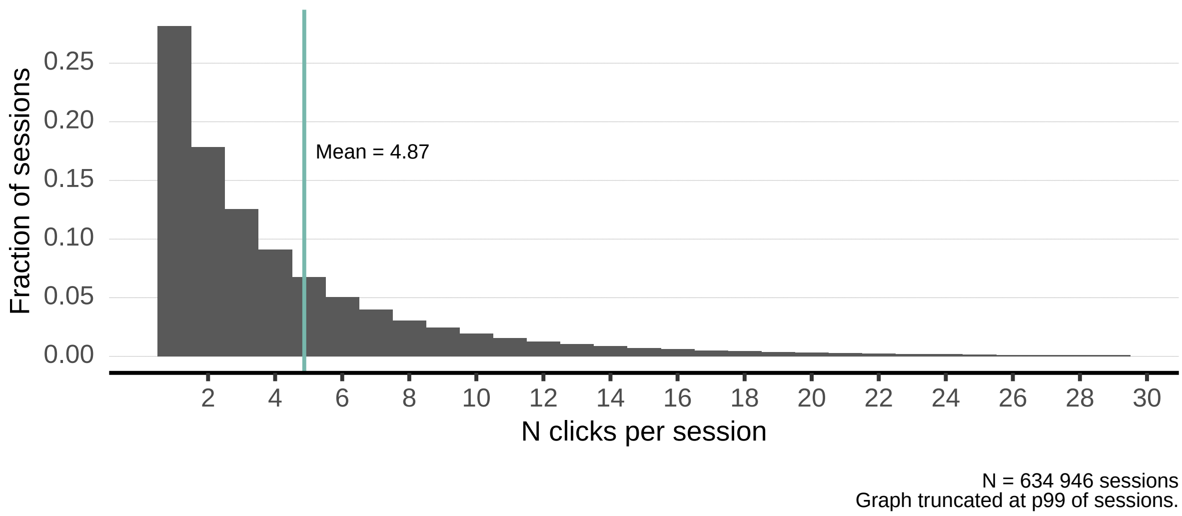

Figure 6: Distribution of the number of clicks per session.

6 Estimates of Employer Market Power

6.1 Methods

We start our analysis assuming that all vacancies receiving clicks are equally attractive in the eyes of workers; think of them as all having the same 'wage', w, so the systematic part of utility is the same in all jobs. In this case labor supply (15) can be written as:

$$\theta_i\left(w_f; \mathcal{F}\right) = \left(\frac{1}{\gamma_i + C_i}\right) \tag{18}$$

where $\gamma_i = e^{\beta(b-w)+\eta_{ui}}$ is a measure of the attractiveness of unemployment relative to work and C_i is the size of the consideration set. Further, assume that $\gamma_i = 0$ which corresponds to the case where all jobs are more attractive than unemployment. These are simplifying assumptions but they require little information beyond the number of clicks and, as we shall see, facilitates comparison with concentration indices which have been widely used in the literature (Azar et al., 2020, 2022b). With this assumption the elasticity at the vacancy level (16) can be written as:

$$\varepsilon_f = \beta\left[1 - \frac{\sum_i \left(\frac{1}{C_i}\right)^2}{\sum_i \left(\frac{1}{C_i}\right)}\right] \tag{19}$$

where the summation is over consideration sets containing firm f. 19 shows that β is important for market power but we do not seek to estimate that here; our interest is in the magnitude of the second term in the square brackets. We refer to this as a concentration index because it has similarities to HHI measures of concentration that have been widely used in the literature. An alternative way of writing (19) is:

$$\varepsilon_f = \beta\left[1 - E\left(\frac{1}{C_i}\right) - \frac{Var\left(\frac{1}{C_i}\right)}{E\left(\frac{1}{C_i}\right)}\right] \tag{20}$$

where the expectations and variances are over the jobseekers who click on this firm. This equation shows that the average number of the reciprocal of the number of clicks matters but also the variance. For a given mean, higher variance implies more market power. In a further special case where all workers have the same size of consideration set, (19) reduces to:

$$\varepsilon_f = \beta\left[1 - \frac{1}{C}\right] \tag{21}$$

Note the second term in square brackets in 21 is the value of the concentration index for equally-sized firms.

Our different measures of employer market power are based on different assumptions about how we measure the size of the consideration sets.

6.2 Baseline Estimates

Our first estimate treats each session as a separate consideration set. This is the approach one would take on a literal reading of the model presented above and with many theoretical models in which all jobs in the current consideration set are available to the workers if they want, they are available immediately and if not taken now, they are no longer available. In each session the unemployed worker has a set of vacancies to consider. If any are better than unemployment the spell ends and the individual disappears from our data set. If none are better then unemployment then the individual remains in our data set but the jobs from this and previous sessions are irrelevant for future consideration because they are worse than unemployment. Each consideration set has a 'now or never' feature. Figure 7 computes the index using this assumption. We only compute this for vacancies with clicks from at least 10 jobseekers as the estimate of the variance will be too low for vacancies clicked on by few workers (see 20). The measured market concentration is very high, the average index value is 4195 which is equivalent to a market of 2.4 recruiting firms with equal market shares.

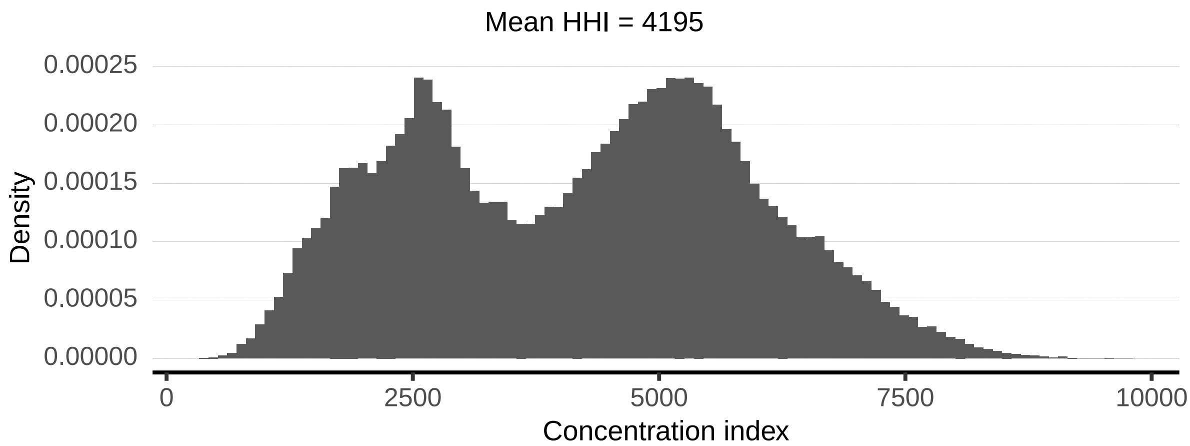

Figure 7: Distribution of the HHI based on Equation 19 over vacancy postings with clicks from more than 10 jobseekers. To compute the HHI, each session is regarded as a separate consideration set.

If every session is separate, the fact that we do not observe sessions outside the job room does not matter under the assumption that, on average, they are the same.

6.3 A Comparison with Concentration Indices

Our measures of the extent of employer market power can be compared to measures of labor market concentration (of vacancies or employment) that have become popular in recent years following the work of Azar et al. (2020) and have been shown for a number of countries to be correlated with wages (e.g. Rinz, 2022). These studies typically define a labor market and then compute HHI for them. Azar et al. (2020) define a labor market as a 6-digit SOC occupation in a commuting zone for a particular period. We can compare these measures with ours. Compared with HHI our measures suggest i) less competition because not all jobs in a labor market are being clicked on, but ii) more competition because we do not impose restrictions that job search is restricted to a specific occupation or area, so markets are wider. Table 2 shows that many jobseekers click on a variety of occupations [8] and in a variety of commuting zones.

Share of clicks (%) in the mode of	Mean	p25	Median	p75
ISCO-08 4-digit	48.1	26.9	43.8	66.7
ISCO-08 3-digit	49.8	28.6	45.7	69.2
ISCO-08 2-digit	53.0	32.9	50.0	72.0
ISCO-08 1-digit	63.0	44.9	61.3	81.8
Commuting zone	76.4	59.8	81.5	95.7

Table 2: Search across market boundaries. For every jobseeker the share of clicks inside the cell with most clicks is computed. The table shows the distribution of the share over jobseekers with 10 or more clicks.

Figure 8 shows that concentration indices are much higher when computed using our measures than when computed using all vacancies in a labor market. However they have a positive correlation of 0.26 (cells weighted by the number of vacancies).

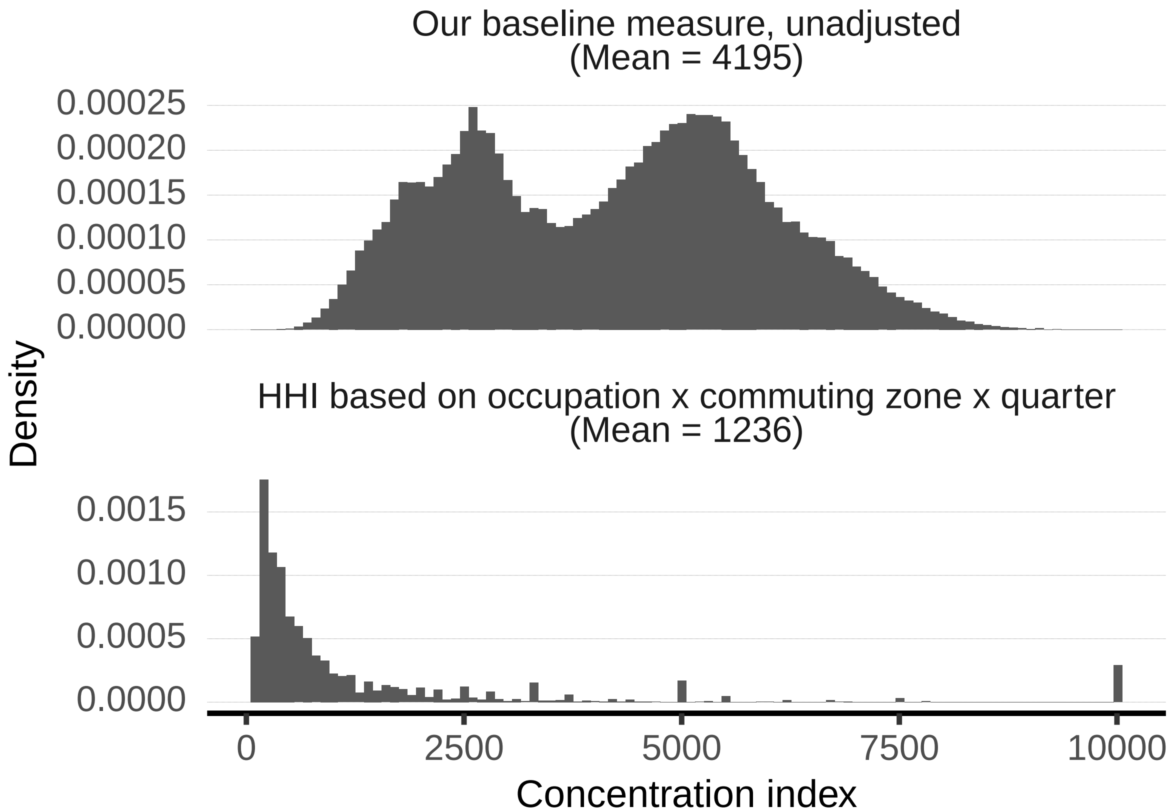

Figure 8: Distribution of the HHI based on Equation 19 over vacancy postings. To compute the HHI, each session is regarded as a separate consideration set.

Figure 9 shows how our measure and the HHI varies over broad occupation categories and regional characteristics.

[8] though Hensvik et al., 2021 find for Sweden that job search was wider in the pandemic so it is possible our findings are not normal.

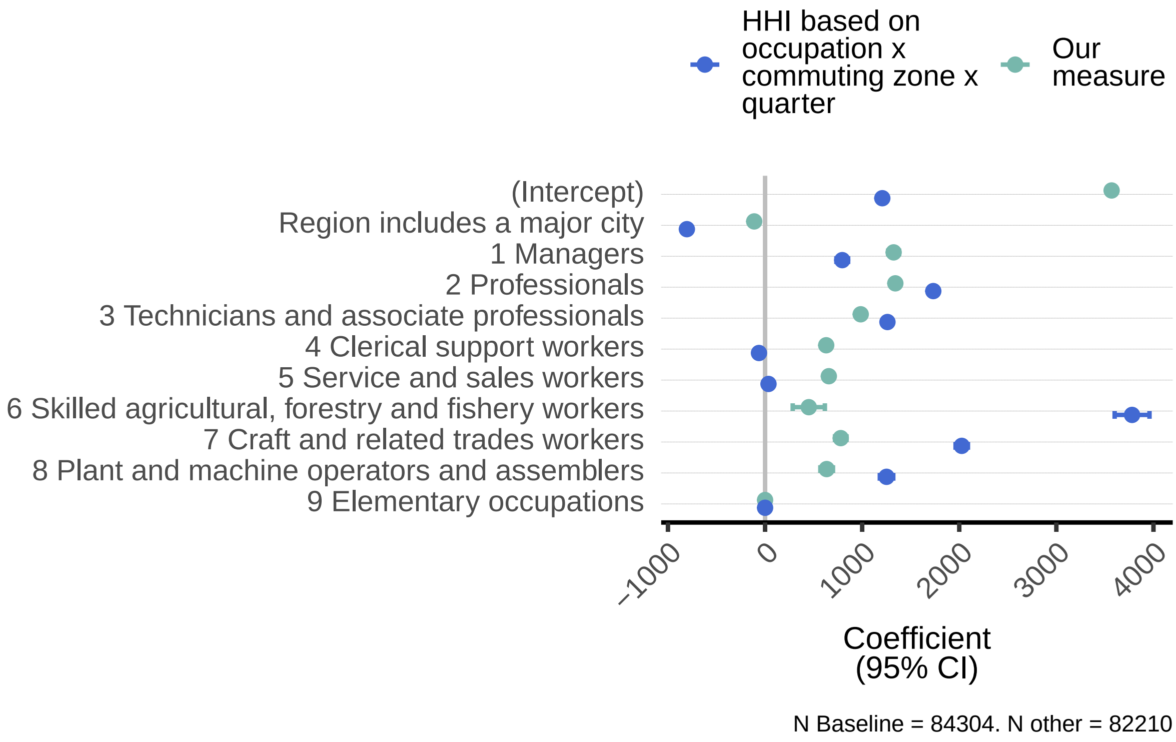

Figure 9: OLS regression of the HHI based on Equation 19 on vacancy characteristics. Major city = 5 biggest cities of Switzerland. Occupations are ISCO-08 definition, 1-digit level.

In general, the patterns of variation are similar but there are some differences. The intercept for our measure is much higher reflecting the generally lower level of competition we find. Labor markets in major cities are more competitive but the extent is smaller in our measure; there are many more vacancies in these areas so the HHI is lower but the number of clicks rises less than proportionally to the number of vacancies. And the labor market for workers in agriculture, forestry and fishing is estimated to be much less competitive using the HHI as compared to our measure; there are few vacancies in this sector but the jobseekers clicking on them are often clicking on vacancies in other occupations.

Our concentration measure is at vacancy level so we also have within-market dispersion. Figure 10 shows how concentration varies across vacancies within the traditional definition of a market. On our measure, jobs with a permanent position, an immediate start and part-time generally have higher levels of concentration.

Our estimates of competition in this section have been based on the assumption that sessions can be treated separately. We next investigate the sensitivity of our conclusions to making a number of different assumptions. We consider what happens if we use broader considerations sets, if we adjust for the fact that we only observe part of search activity and if we adjust for the fact that not all applications will be successful.

6.3.1 Broader Consideration Sets

If it takes time for applications to be resolved, the size of the consideration set in a single session will be too small as consideration sets in the past may still be 'in play' and future consideration

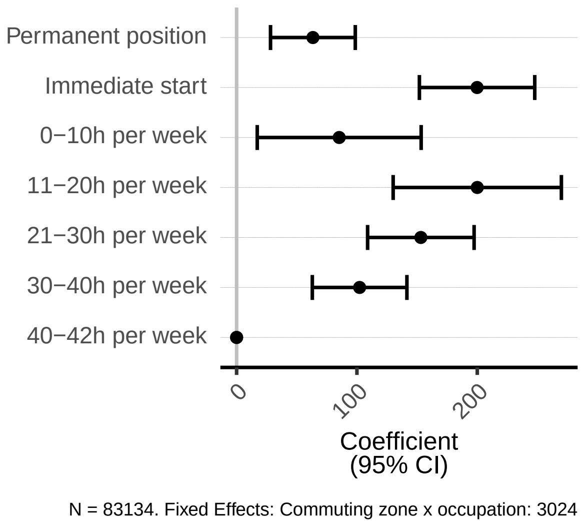

Figure 10: OLS regression of the HHI based on Equation 19 on vacancy characteristics conditional on the occupation (ISCO-08 4-digit) x commuting zone cell.

set may be relevant to whether current jobs are taken. A too narrow definition of consideration sets will lead to an over-statement of labor market concentration.

We consider two broader measures of consideration sets. First, we go to the extreme and use as the consideration set all vacancies clicked on by the jobseeker whenever this occurred. Each jobseeker then has one, much larger, consideration set. This may go too far as jobs that were clicked on in the past may no longer be available (the median duration of a vacancy is 60 days). We have data on the time of the click on the vacancy and the date the vacancy was taken off the portal. So, as an alternative, for each vacancy a job seeker considers, we construct a consideration set that features all jobs that the jobseeker has already clicked on and which are still online and all jobs that the jobseeker will click on before the considered vacancy is taken off the portal. This measure can be seen as assuming that vacancies are open as long as they are on the platform and not longer available when they are removed from the platform.

6.3.2 Correcting the Estimate of λ

To construct the measure of competition based on treating sessions separately, it does not matter that we do not observe job search on other platforms as long as the sessions we observe are representative of all sessions. But, for the measures that group sessions it does matter. If the consideration set is all vacancies ever clicked on, unobserved search activity will lead to an under-statement of the size of the consideration set[9]. One can think of this problem as being that there are more sessions than those we observe i.e. λ, the frequency of sessions being under-estimated.

Suppose that the arrival rate of sessions on the platform is λ and the arrival rate of sessions on other platforms $\lambda_o(\lambda)$ which we allow to depend on λ as searchers may differ in the extent to which they use the job room. The overall arrival rate of sessions is then $[\lambda + \lambda_o(\lambda)]$. If we assume

[9]The problem that only a sub-set of search is observed is common to many other studies e.g. those of applications

that sessions in the job room are equally effective as sessions elsewhere (a reasonable baseline assumption) the probability a job is obtained through the job room is given by $\rho = \frac{\lambda}{\lambda + \lambda_o(\lambda)}$. If we knew ρ we would want to use λ/ρ as the 'true' frequency of job sessions.

To obtain an estimate of ρ we use the fact that we observe the re-employment job and can see whether this is at a firm where we have observed a click. On average the probability that the firm of the re-emplyoment job is among the clicked vacancies on the job room is 4.6% but there is a lot of variation across individuals. Figure 11 shows how the probability varies with activity on the job room.

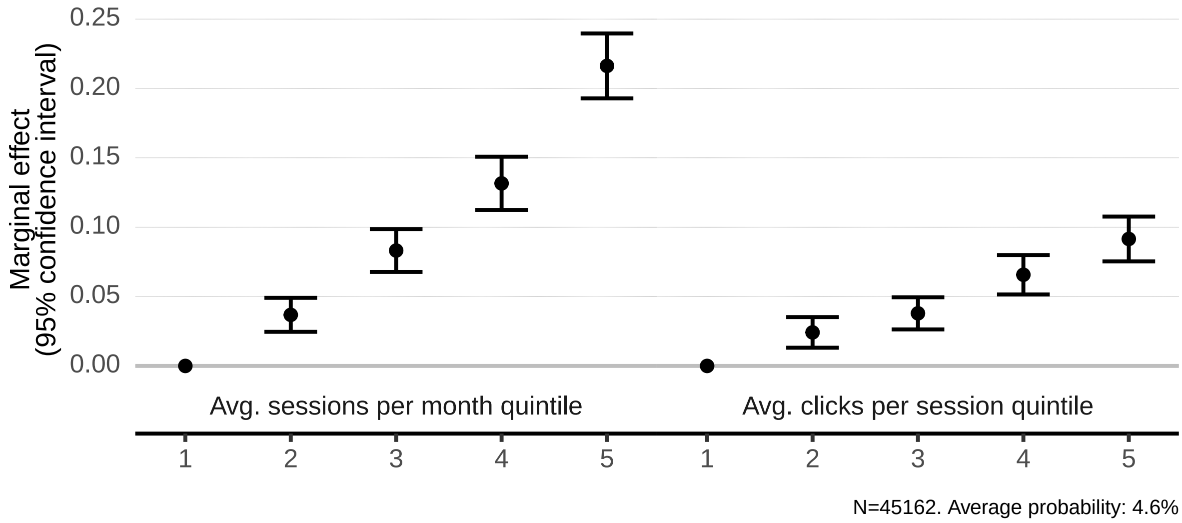

Figure 11: Marginal effects (at means) from a logistic regression. The outcome is a binary variable whether a jobseekers' new firm (after the unemployment spell) is among the firms in the clicked vacancy postings.

The baseline probability - for jobseekers in the bottom quintiles of the session rate and the number of clicks per session - is 0.9%; these are probably jobseekers who use the job room very little. Jobseekers with more activity in the job room are more likely to obtain a job they clicked on in the job room. The predicted probabilities is around 24.5% for the jobseekers in the highest quintiles of the session rate and the number of clicks per session. The strongest predictor is the frequency of job room-sessions rather than the average number of clicks per session.

6.3.3 Correcting the Estimate of C

As is common in many models of monopsony, the framework developed above assumes that workers can freely choose every employer in their consideration set. In reality, we know that many job applications are rejected so the number of clicks represents an over-estimate of the number of jobs the searcher actually has to choose from [10].

A simple correction to allow for this is to weight clicks by their probability of being successful, which will be related to the total number of clicks on the vacancy. Define $C_{ij} = 1$ if individual i clicks on vacancy j and p_{ij} to be the probability of success. From the perspective of firm f the jobseeker considering firm f have consideration sets consisting of f and a probability weighted

[10] The directed search literature - see Wright et al., 2021 - explicitly takes account of this

sum of all other firms considered so that the size is given by:

$$C_{ik}^{a} = C_{ik} + \sum_{j \neq k} p_{ij} C_{ij} \tag{22}$$

The intutition is the following. If jobseekers interested in this firm are also interested in 10 others but have a 10% chance of being offered those jobs, effectively there is only 1 other job being considered. In this formulation clicks on the vacancy being considered are not down-weighted by the probability of success because what is relevant for them is the number of applicants who do not have a better offer it is up to them to decide who to accept.

The 'HHI' for vacancy f would then be given by:

$$HHI_f = \frac{\sum_i \left(\frac{1}{C_{if}^{a}} \right)^2}{\sum_i \left(\frac{1}{C_{if}^{a}} \right)} \tag{23}$$

where the sum is over all individuals who click on vacancy f. To implement this we estimate p_{ij} in the following way. The total number of clicks for vacancy j is $A_j = \sum_i C_{ij}$. If a vacancy with A_j clicks in total (something we observe) leads to $R(A_j)$ recruits then the probability of an individual click being successful is $R(A_j)/A_j$. In the case where all vacancies lead to one hire the probability of an individual applicant getting a job is $p_j = 1/A_j$. This probability can be computed using all observed clicks not just from our sample of the unemployed. One might want to make a further adjustment for the fact that some clicks on a vacancy will be from other platforms; we do not do that for the moment.

6.3.4 Adjust for usage of job-room.ch

In our measures, a jobseeker with very few clicks on the portal will heavily influence the vacancy-level HHI. This is because of the double role of 1/C, as i) the weight a jobseeker receives in the computation of the vacancy's average, and ii) as an indicator for the 'market share' of the vacancy in the jobseeker's choice (see eq. 17). However, one could argue that jobseekers with very few clicks are not 'seriously' searching for work on the job-room.

A further correction, therefore, weights down jobseekers who have a low probability of finding employment from their search on the job-room. The weight is an estimate of the probability of finding employment from a click on the portal. In any given month, it is modeled as the probability of finding employment the next month, given the click history on job-room.ch, multiplied by the probability that the firm of the re-employment job is among the clicked vacancies on the job room, ρ from Section 6.3.2.

The probability of finding a job within the next month, given the number of clicks, is obtained from a monthly hazard model. The outcome is the hazard of finding employment the next month, $t+1$, modeled using a complementary log–log specification, $1 - h(x\beta) = e^{-e^{x\beta}}$. The explaining variables are the lags of the number of clicks on job-room in $t-1, t-2, ..$

Figure 12 shows the result of the hazard model. We find that more clicks are associated with a higher unemployment probability and that only clicks two to three months ago have an effect. 10 clicks in month t lead to a 1.2% increase in the exit probability three months later.

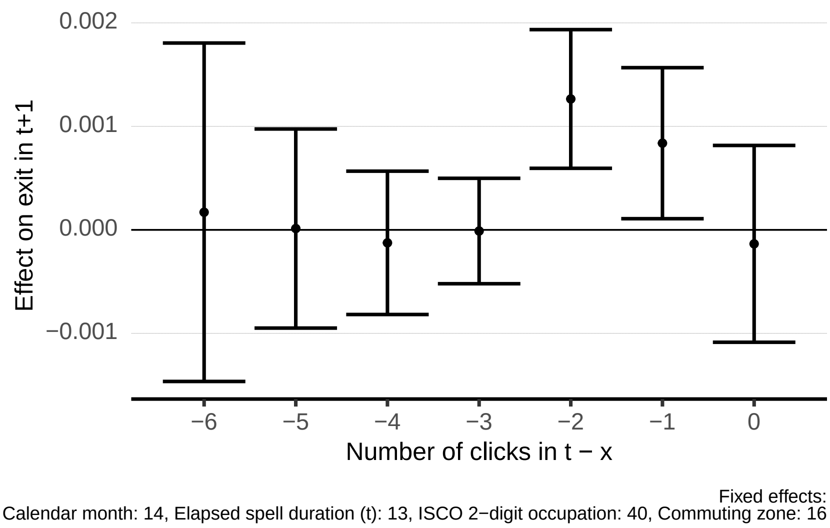

Figure 12: Coefficients from a monthly complementary log-log hazard model. The outcome is whether the jobseeker finds employment in the next month.

6.4 Corrected Measures of Labor Market Concentration

Table 3 presents some summary statistics on different measures of labor market concentration.

	(1)	(2)	(3)	(4)
Separate consideration sets by session	4195	4195	8700	8700
One consideration set by spell	1034	28	5074	569
All clicked and online vacancies in consideration set	1375	67	6156	859
Adjusted for other search channels (λ)		X		X
Adjusted for rejection (C)			X	X

Table 3: Mean vacancy-level HHI for different measures and corrections

The level of concentration is affected by the assumptions made. As expected, broader definition of the consideration set, and adjusting for unobserved job search has the effect of reducing measured concentration, often by a large amount. But correcting for the probability of success moves things in the opposite direction.

To give some idea of the impact of different corrections Figure 13 compares the unadjusted version of our measure, based on equation 19 to two other measures based on broader consideration sets and adjusted for unobserved search and the job finding probability.

The baseline measure has a mean of 4195 suggesting that jobseekers are only considering about 2.4 firms. When adjusting for a broader consideration set, when all clicks are included the mean is 1034 (equivalent to about 10 firms) and when looking at the set of clicked and online vacancies it is 1375 (equivalent to about 7 firms).

Figure 14 looks at the effect of down-weighting sessions of jobseekers not very actively using the job-room. The graph shows that this adjustment reduces the bi-modality of the HHI distribution. The mean concentration index after this adjustment is slightly lower than the unadjusted measure, at 3751, equal to 2.7 firms competing for a worker.

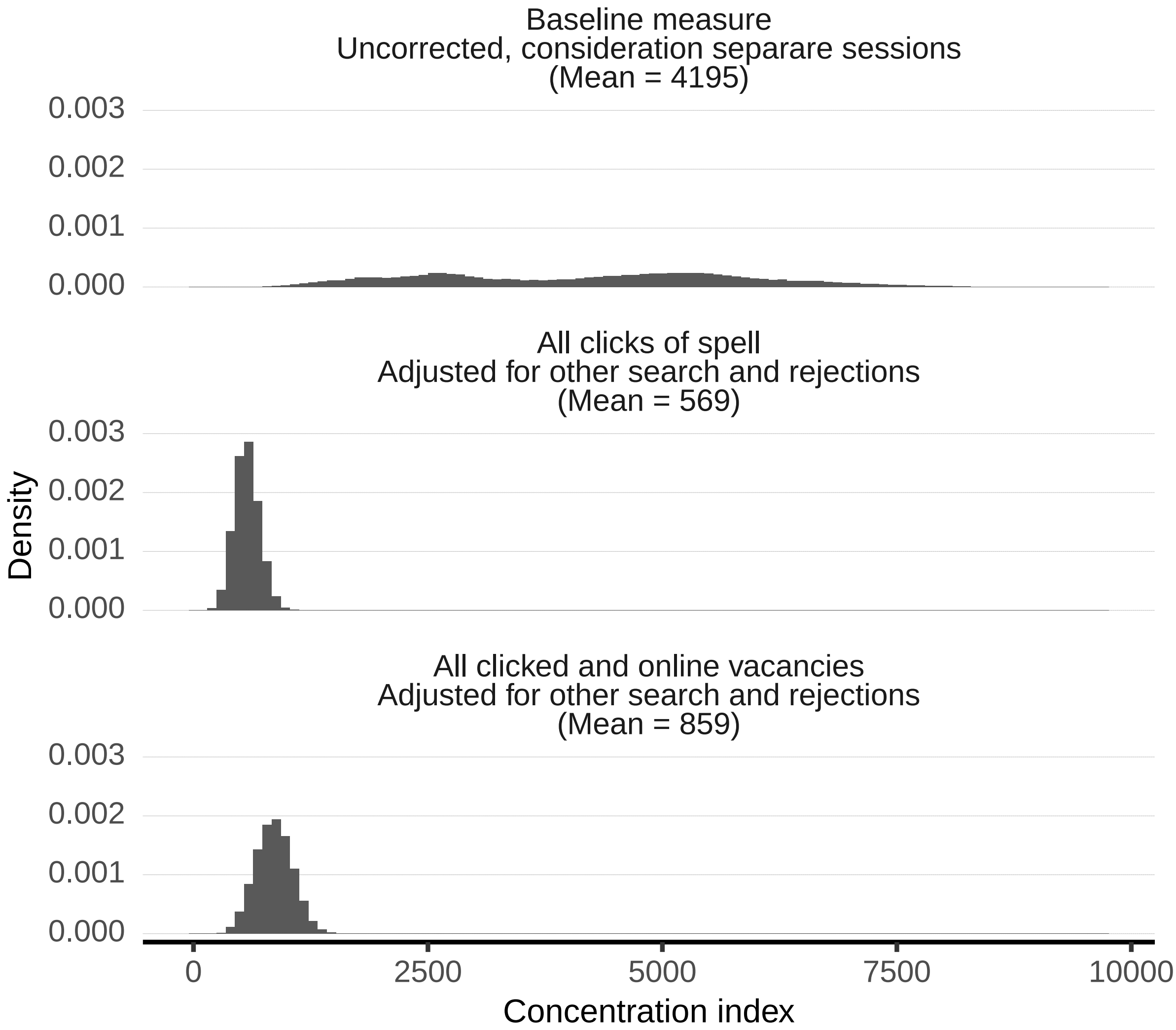

Figure 13: Distribution of the HHI with different corrections

6.5 Recurring vacancies and firms in the consideration set

12% of clicked vacancies are clicked by a jobseeker in more than one session. Our baseline measure assumes that these vacancies are fully considered again in the subsequent sessions and includes them as separate observations in the index computation. However, one might argue that this overestimates the choice a jobseeker has. Figure 15 compares the baseline measure to a version, where only the first click on a vacancy is counted towards the consideration sets, all subsequent clicks are ignored. The figure also shows a version of the HHI where each firm is only considered once and clicks on already-seen firms are not counted to the consideration set. These adjustments yield slightly higher estimates of employer market power. The correlation between the baseline and the adjusted measures is 0.84 and 0.62, respectively.

6.6 Varying Click 'Quality'

So far we have assumed that all clicks were equally effective in sustaining labor market competition; implicitly the formulae used were based on the assumption of a symmetric equilibrium in

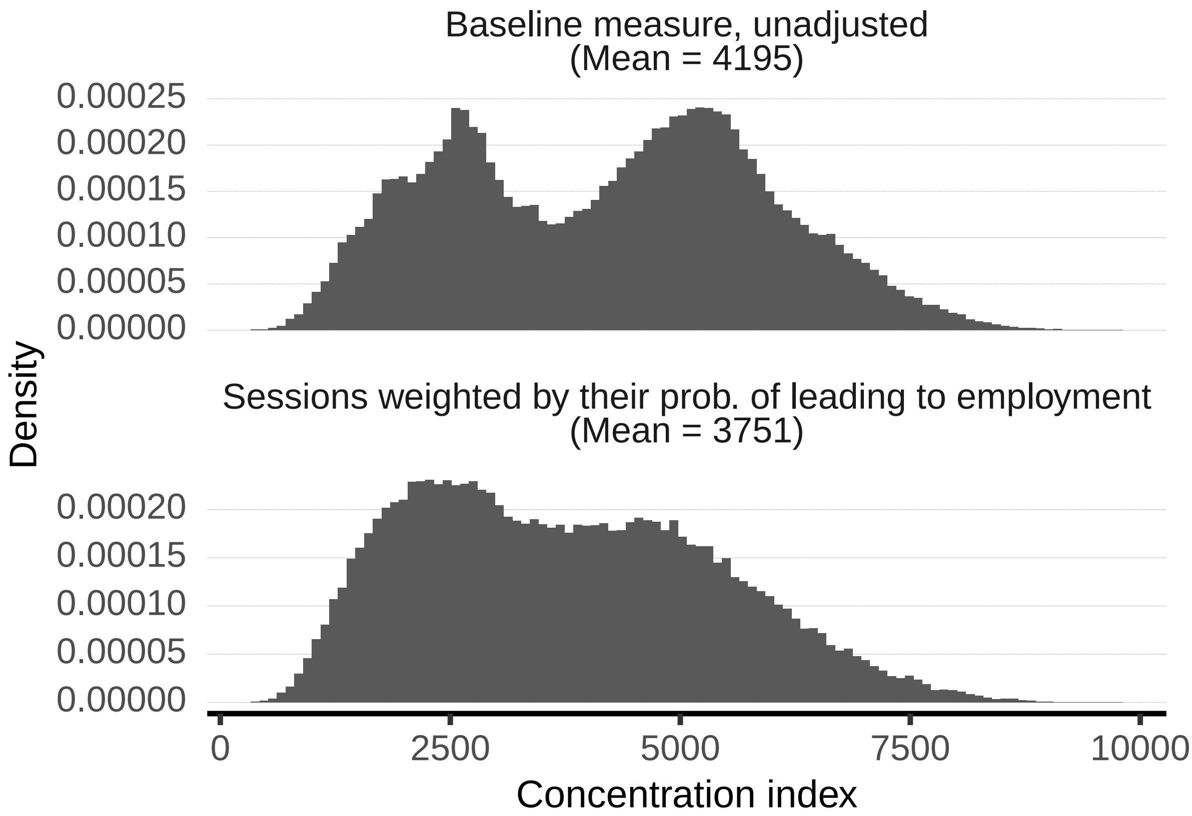

Figure 14: Distribution of the HHI with a downweighting for sessions by jobseekers not very actively using the job portal.

which all firms were identical. In reality, not all firms are equally attractive to workers and this section investigates whether taking account of that matters for the measures of market power.

Continue to maintain the assumption that unemployment is always unattractive but now allow for job vacancies to differ in their attractiveness to workers. In this case (15) can be written as:

$$\theta_i \left(w_f; \mathcal{F}\right) = \frac{e^{\beta w_f}}{\sum_{j \epsilon \mathcal{F}_i} e^{\beta w_j}} \tag{24}$$

This can then be aggregated to the vacancy level using (19) to give

$$\varepsilon_f = \beta \frac{\sum_i \theta_i \left(w_f; \mathcal{F}\right) \left[1 - \theta_i \left(w_f; \mathcal{F}\right)\right]}{\sum_i \theta_i \left(w_f; \mathcal{F}\right)} = \beta \left[1 - \frac{\sum_i \theta_i \left(w_f; \mathcal{F}\right)^2}{\sum_i \theta_i \left(w_f; \mathcal{F}\right)}\right] \tag{25}$$

This has similarities to earlier formula but now jobs that workers are more interested in attract a greater weight i.e. they loom larger in the worker's consideration set though they may not necessarily be larger employers. To implement this we use the following method. First, think of w_f as being all the systematic factors that make a job more attractive to a worker. We take the sample of 5173 jobseekers who end up in employment at a firm we observe they have clicked on. We then estimate a multinomial logit model for the successful click relative to the others. The explanatory variables are the geographical distance to the job, the occupational

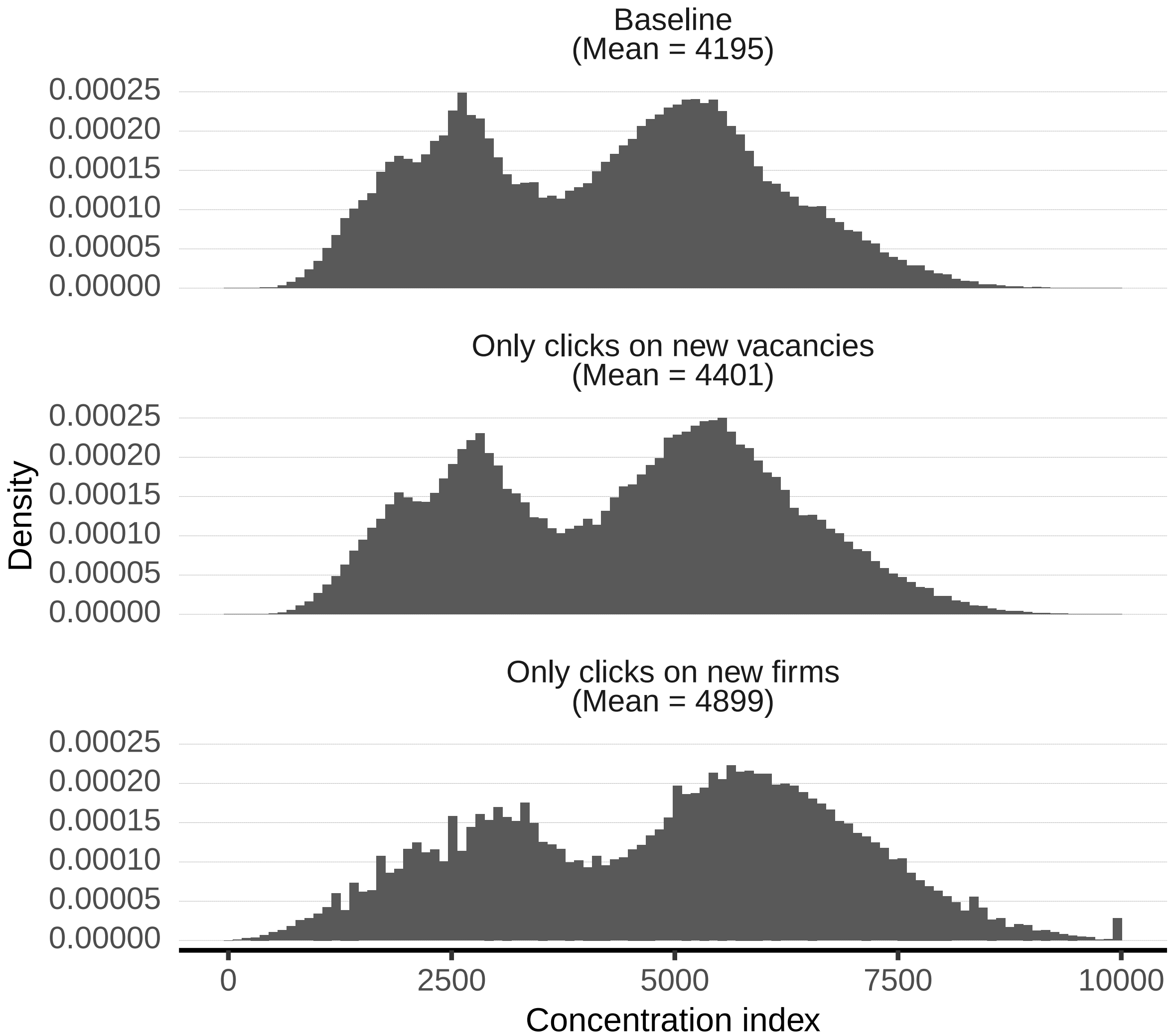

Figure 15: Distribution of the HHI with different treatment of re-occurring vacancies and firms.

distance to the job (Klaeui et al., 2024) as well as whether the hours worked correspond to the jobseeker's stated preference in hours worked[11]. We allow for a flexible functional form for the continuous variables.

The estimates imply that a better match in location, occupation and hours worked increases the probability of taking up employment at a particular job. To give a flavour of the model imagine a hypothetical consideration set of 5 firms where 4 jobs have the median match in occupation, location and desired hours but one job is in the first distance quintile. The closer job would have a match probability of 23% and the other 4 jobs a probability of 19% each. The same exercise for occupational distance and desired working hours leads a very similar pattern of market shares.

We will refer to the predicted value of the utility of a vacancy to an individual as job quality.

We then use these estimates to compute (24) and this can then be used in the formula (19) to provide an alternative measure of employer market power over unemployed workers. Figure

[11] In the first meeting with a caseworker, at the start of the unemployment spell, a jobseeker's desired hours worked per week are recorded among other information.

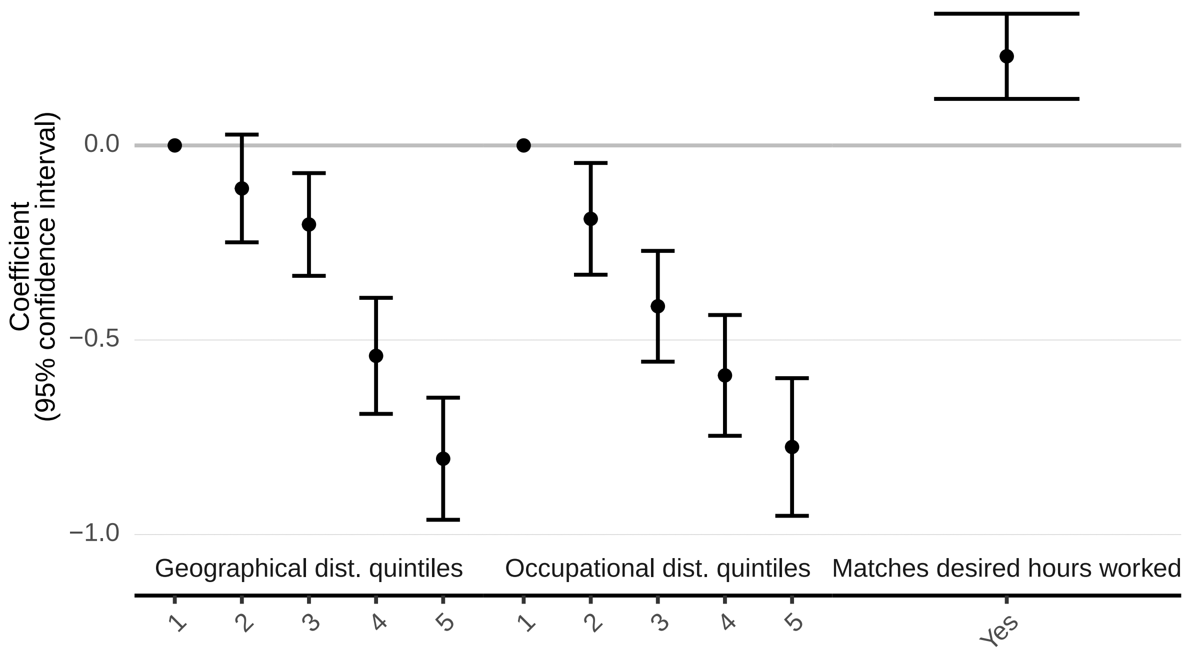

Figure 16: Coefficients from an multinomial logit regression. The dependent variable is whether the jobseeker finds a job at a firm or not and the choice set are all clicked vacancy postings. The sample consists of the 5106 jobseekers who find a job at one of the clicked firms and don't have missing information on the distance to the job found. If multiple vacancy postings in a choice set belong to the firm where a jobseeker finds a job, the dependent variable is set to 1 for all those jobs.

17 compares the distribution of the index allowing for vacancy heterogeneity with our baseline index. Both are computed regarding each session as a separate consideration set.

The results show that allowing for vacancy heterogeneity has little impact on the concentration measure. The average concentration is almost the same as for the baseline measure and the correlation coefficient between the two measures is 0.99. The similarity between the two versions also holds for the indices computed with different consideration set definition. These results suggest that the quantity of jobs considered by a jobseeker is the main driver of market power and that variation in quality relatively unimportant.

7 Job Search to Sustain Labor Market Competition; Too Little or Too Narrow?

jobseekers have an incentive to search to find more attractive work faster. But, if wage determination is not individualized, individuals do not have a strong incentive to search to make labor markets more competitive as most of the benefits would flow to others (though there would also be costs for employers). In recent years there have been a number of evaluations of policies designed to increase the job search of the unemployed and make it broader (e.g Belot et al., 2019; Klaauw and Vethaak, 2022; Dhia et al., 2022). These report mixed outcomes.

Increasing the quantity of job search is likely to increase competition on labor markets.

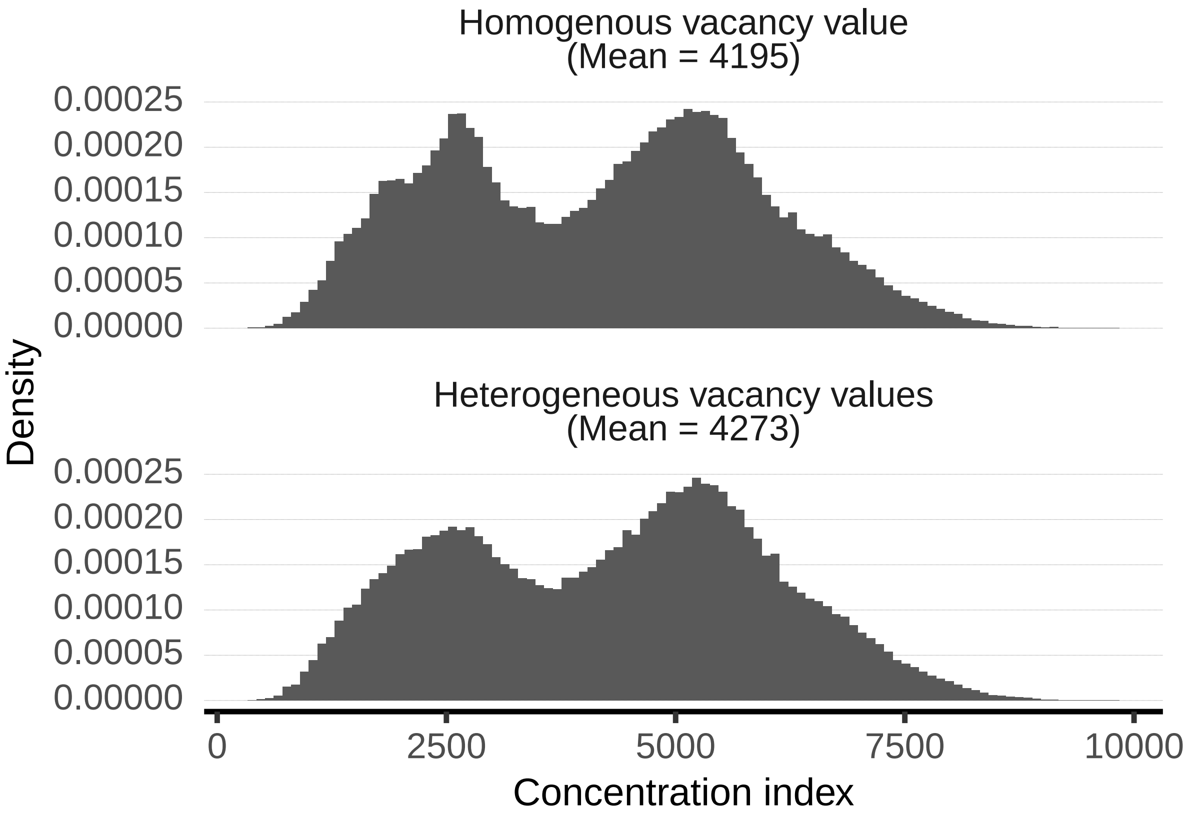

Figure 17: Distribution of the HHI based on Equation 19 over vacancy postings. To compute the HHI, each session is regarded as a separate consideration set.

But increasing the breadth of job search many not have positive effects if it means workers considering more jobs in which they have little interest or prospect of getting. In terms of the framework laid out above, competition is maximized for a given number of clicks if those clicks have the same probability of resulting in a job. A key question is whether it is feasible for jobseekers to increase the quantity of job search without sacrificing quality.

To shed some light on this we use the estimated coefficients from the model of the previous section to compute the predicted job quality for all individuals in all vacancies, whether or not they have been clicked. There is strong evidence that the jobs that are clicked on are directed towards those with higher job quality. We compare the actual distribution of job quality in clicks with what would be found using the same number of clicks but choosing the vacancies at random[12]. Comparing Figure 18 (1) and (2) shows this does much worse that the observed clicks implying that job search is directed towards jobs the searcher finds more appealing; this is not surprising.[13]

But could search be better-directed? To answer this question, we take random sets of vacancies of a certain size and choose the 'best' set of jobs equal to the actual number of clicks,

[12]We sample the random vacancies from the distribution of vacancies with at least one click and we sample at the jobseeker-month level. This ensures that the vacancies were available to the jobseeker at the time of their search.

[13]Analogous to the computation of the inclusive value in a nested logit model, the average value is computed the following way $\bar{v}_i = log(1/N * \sum_j exp(v_{ij}))$

this is shown in specification (3) in Figure 18. What is perhaps surprising is that there does not seem to be much gain from doing this. This is even more striking when one considers that the jobs that are clicked are likely to have some component of utility observable to the searcher but not the researcher.

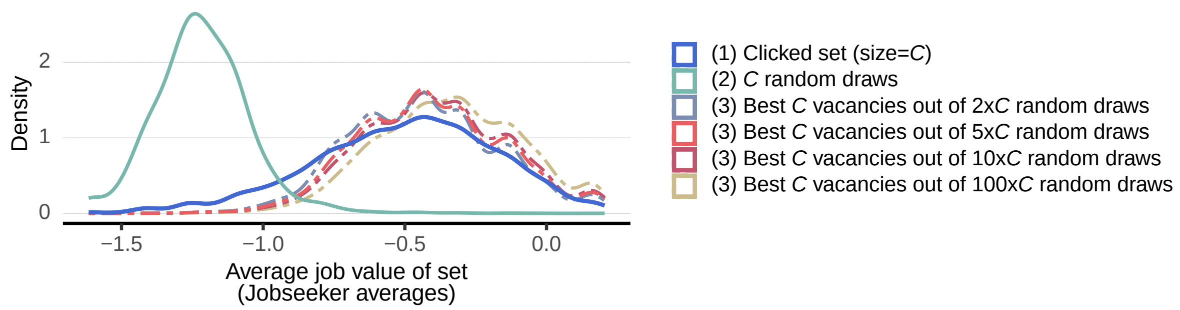

Figure 18: Average job value of different sets of vacancies. Averages by jobseeker. The value is computed analogous to the inclusive value from a logit model, $\bar{v}_i = log(1/N * \sum_j exp(v_{ij}))$, using the estimates from Section 6.6

.

How does the average quality vary across sessions; does it decline? Figure 19 shows that the average value per session in each month doesn't follow a clear trend. The large standard errors suggest that the average value of a session in a given month varies a lot over jobseekers.

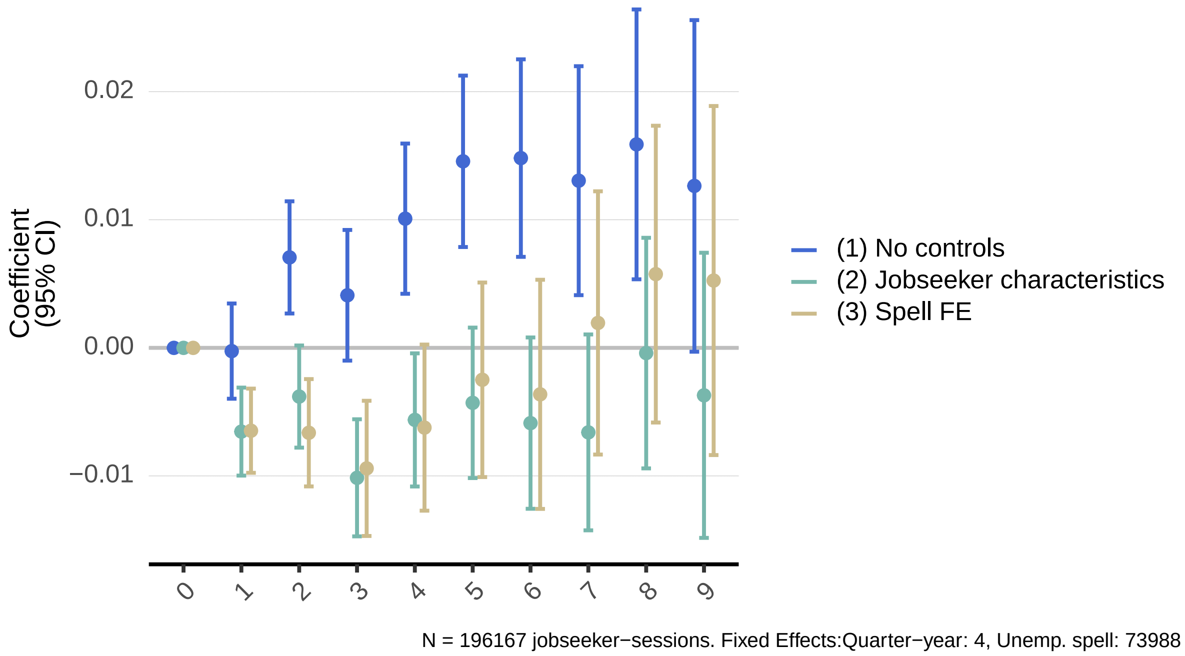

Figure 19: OLS regressions of the average value per session on the elapsed month of unemployment spell. The regressions are conditional on having at least one session in a month. The regressions exclude jobseekers with an unemployment spell shorter than 60 days. The value is computed analogous to the inclusive value from a logit model, $\bar{v}_i = log(1/N * \sum_j exp(v_{ij}))$, using the estimates from Section 6.6.

These results suggest that job search activity could be increased without any clear loss in quality i.e. the unemployed are not clicking on all the available jobs that we think they might be interested in.

8 Conclusion

We have argued that job search is likely to be important in sustaining competition in labor markets. The larger the set of firms being considered by jobseekers, the more competitive the market is likely to be. Most theoretical models of employer market power make assumptions about the consideration sets of jobseekers, either that they are the universe of firms in a labor market (in the new classical models) or that opportunities arrive one at a time (in the modern monopsony models based on frictions). This paper has tried to assess how large consideration sets actually are. We present a framework to develop indices of labor market concentration akin to, but different from, the commonly used HHI indices. We then compute these indices using data on Swiss UI recipients search activity on a platform, using clicks on vacancies to define their consideration sets. We discuss how these indices are affected by different assumptions that could be made about the search process.

References

Jason Abaluck and Abi Adams-Prassl. What do consumers consider before they choose? identification from asymmetric demand responses *. doi: 10.1093/qje/qjab008. URL `https://academic.oup.com/qje/article/136/3/1611/6169736`.

Pawel Adrjan and Reamonn Lydon. Clicks and jobs: measuring labour market tightness using online data, 2019.

José Azar, Ioana Marinescu, Marshall Steinbaum, and Bledi Taska. Concentration in us labor markets: Evidence from online vacancy data. *Labour Economics*, 66:101886, 2020. ISSN 0927-5371. doi: https://doi.org/10.1016/j.labeco.2020.101886. URL `https://www.sciencedirect.com/science/article/pii/S0927537120300907`.

José Azar, Steven Berry, and Ioana Marinescu. Estimating labor market power, 8 2022a.

José Azar, Ioana Marinescu, and Marshall Steinbaum. Labor market concentration. *Journal of Human Resources*, 57:S167, 4 2022b. doi: 10.3368/jhr.monopsony.1218-9914R1. URL `http://jhr.uwpress.org/content/57/S/S167.abstract`.

Mark Bagnoli and Ted Bergstrom. Log-concave probability and its applications. *Economic Theory*, 26:445–469, 2005. ISSN 09382259, 14320479. URL `http://www.jstor.org/stable/25055959`.

Stefano Banfi and Benjamín Villena-Roldán. Do high-wage jobs attract more applicants? directed search evidence from the online labor market. *Journal of Labor Economics*, 37:715–746, 1 2019. ISSN 0734-306X. doi: 10.1086/702627. URL `https://doi.org/10.1086/702627`. doi: 10.1086/702627.

Michèle Belot, Philipp Kircher, and Paul Muller. Providing advice to jobseekers at low cost: An experimental study on online advice. *The Review of Economic Studies*, 86:1411–1447, 7 2019. ISSN 0034-6527. doi: 10.1093/restud/rdy059. URL `https://doi.org/10.1093/restud/rdy059`.

David Berger, Kyle Herkenhoff, and Simon Mongey. Labor market power. *American Economic Review*, 112:1147–1193, 4 2022. ISSN 0002-8282. doi: 10.1257/aer.20191521.

Steven Berry and Ariel Pakes. The pure characteristics demand model*. *International Economic Review*, 48:1193–1225, 11 2007. ISSN 0020-6598. doi: https://doi.org/10.1111/j.1468-2354.2007.00459.x. URL `https://doi.org/10.1111/j.1468-2354.2007.00459.x`. https://doi.org/10.1111/j.1468-2354.2007.00459.x.

V Bhaskar and Ted To. Minimum wages for ronald mcdonald monopsonies: A theory of monopsonistic competition. *The Economic Journal*, 109:190–203, 1999. ISSN 00130133, 14680297. URL `http://www.jstor.org/stable/2565930`.

Kenneth Burdett. A useful restriction on the distribution of wage offers, 1981.

Kenneth Burdett and Dale T Mortensen. Wage differentials, employer size, and unemployment. *International Economic Review*, 39:257–273, 1998. ISSN 00206598, 14682354. doi: 10.2307/2527292. URL http://www.jstor.org/stable/2527292.

David Card, Ana Rute Cardoso, Joerg Heining, and Patrick Kline. Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36:S13–S70, 12 2017. ISSN 0734-306X. doi: 10.1086/694153. URL https://doi.org/10.1086/694153. doi: 10.1086/694153.

Stefano DellaVigna, Jörg Heining, Johannes F Schmieder, and Simon Trenkle. Evidence on job search models from a survey of unemployed workers in germany. *The Quarterly Journal of Economics*, 137(2):1181–1232, 2022.

Aïcha Ben Dhia, Bruno Crépon, Esther Mbih, Louise Paul-Delvaux, Bertille Picard, and Vincent Pons. Can a website bring unemployment down? experimental evidence from france, 4 2022.

Michael Dinerstein, Liran Einav, Jonathan Levin, and Neel Sundaresan. Consumer price search and platform design in internet commerce. *American Economic Review*, 108:1820–1859, 7 2018. ISSN 0002-8282. doi: 10.1257/aer.20171218.

R. Jason Faberman and Marianna Kudlyak. The intensity of job search and search duration. *American Economic Journal: Macroeconomics*, 11:327–357, 7 2019. ISSN 1945-7707. doi: 10.1257/mac.20170315.

Michelle Sovinsky Goeree. Limited information and advertising in the u.s. personal computer industry. *Econometrica*, 76:1017–1074, 2008. ISSN 00129682, 14680262. URL http://www.jstor.org/stable/40056493.

Lena Hensvik, Thomas Le Barbanchon, and Roland Rathelot. Job search during the covid-19 crisis. *Journal of Public Economics*, 194:104349, 2021. ISSN 0047-2727. doi: https://doi.org/10.1016/j.jpubeco.2020.104349. URL https://www.sciencedirect.com/science/article/pii/S0047272720302139.

Elisabeth Honka, Ali Hortaçsu, and Matthijs Wildenbeest. Empirical search and consideration sets. 1:193–257, 1 2019. ISSN 2452-2619. doi: 10.1016/BS.HEM.2019.05.002.

Gregor Jarosch, Jan Sebastian Nimczik, and Isaac Sorkin. Granular search, market structure, and wages, 9 2019.

Bas Van Der Klaauw and Heike Vethaak. Empirical evaluation of broader job search requirements for unemployed workers, 2022. URL www.iza.org.

Jeremias Klaeui, Daniel Kopp, Rafael Lalive, and Michael Siegenthaler. Adapting to scarcity: Job search and recruiting across occupational boundaries. *University of Lausanne and ETH Zurich*, 2024.

Thibaut Lamadon, Magne Mogstad, and Bradley Setzler. Imperfect competition, compensating differentials, and rent sharing in the us labor market. *American Economic Review*, 112: 169–212, 1 2022. ISSN 0002-8282. doi: 10.1257/aer.20190790.

David Liechti, Mirjam Suri, Thomas Möhr, Patrick Arni, and Michael Siegenthaler. Methoden der Stellensuche und Stellensucherfolg. *Grundlagen für die Wirtschaftspolitik Nr. 33. Staatssekretariat für Wirtschaft SECO, Bern, Schweiz*, 2020.

Alan Manning. The real thin theory: monopsony in modern labour markets. *Labour Economics*, 10:105–131, 4 2003. ISSN 0927-5371. doi: 10.1016/S0927-5371(03)00018-6.

Alan Manning. Monopsony in labor markets: A review. *ILR Review*, 74:3–26, 6 2020. ISSN 0019-7939. doi: 10.1177/0019793920922499. URL https://doi.org/10.1177/0019793920922499. doi: 10.1177/0019793920922499.

Kevin Rinz. Labor market concentration, earnings, and inequality. *Journal of Human Resources*, 57:S251, 4 2022. doi: 10.3368/jhr.monopsony.0219-10025R1. URL http://jhr.uwpress.org/content/57/S/S251.abstract.

Randall Wright, Philipp Kircher, Benoît Julien, and Veronica Guerrieri. Directed search and competitive search equilibrium: A guided tour. *Journal of Economic Literature*, 59:90–148, 3 2021. ISSN 0022-0515. doi: 10.1257/jel.20191505.

Appendix A

8.1 Proof of Proposition 1

8.1.1 Proof of Proposition 1.1

Both $H\left(\right)$ and $G_u\left(\right)$ are increasing in w_f so (4) shows $n\left(w_f;\mathcal{F}\right)$ is.

8.1.2 Proof of Proposition 1.2

$H\left(\right)$ and $G_u\left(\right)$ are log-concave implies $H\left(\right)G_u\left(\right)$ is log-concave. And $n\left(w_f;\mathcal{F}\right)$ is then a linear combination of log-concave functions which is known to also be log-concave. Log-concavity of $n\left(w_f;\mathcal{F}\right)$ implies that the elasticity of $n\left(w_f;\mathcal{F}\right)$ with respect to w_f $\frac{\partial logn\left(w_f;\mathcal{F}\right)}{\partial w_f}$is a decreasing function of w_f.

8.1.3 Proof of Proposition 1.3

Suppose we have a set $\mathcal{F}$ and add an extra firm j to it. Using (4) and (2) Labor supply to the firm can now be written as:

$$n\left(w_f;\mathcal{F}\cup\{j\}\right)=\int_{\eta_{min}}^{\eta_{max}}g\left(\eta\right)H\left(\beta w_f+\eta;\mathcal{F}\backslash\{f\}\right)G\left(\beta\left(w_f-w_j\right)+\eta\right)G_u\left(\beta\left(w_f-b\right)+\eta\right)d\eta \tag{26}$$

To minimize notation define $Z\left(\beta w_f+\eta\right)=H\left(\beta w_f+\eta;\mathcal{F}\backslash\{f\}\right)G_u\left(\beta\left(w_f-b\right)+\eta\right)$. $Z\left(\beta w_f+\eta\right)$ will be an increasing log-concave function. Then (26) can be written as:

$$n\left(w_f;\mathcal{F}\cup\{j\}\right)=\int_{\eta_{min}}^{\eta_{max}}g\left(\eta\right)Z\left(\beta w_f+\eta\right)G\left(\beta\left(w_f-w_j\right)+\eta\right)d\eta \tag{27}$$

Define a variable y as:

$$y\left(\eta,w_f\right)=\frac{\int_{\eta_{min}}^{\eta}g\left(x\right)Z\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z\left(\beta w_f+x\right)dx}=\frac{\int_{\eta_{min}}^{\eta}g\left(x\right)Z\left(\beta w_f+x\right)dx}{n\left(w_f;\mathcal{F}\right)} \tag{28}$$

For future use denote the inverse of this function as $\eta\left(y,w_f\right)$. Differentiating (28) we have that:

$$n\left(w_f;\mathcal{F}\right)dy=g\left(\eta\right)Z\left(\beta w_f+\eta\right)d\eta \tag{29}$$

Using (29) to changing the variable of integration in (27) from η to y we have that:

$$n\left(w_f;\mathcal{F}\cup\{j\}\right)=n\left(w_f;\mathcal{F}\right)\int_0^1 G\left[\beta\left(w_f-w_j\right)+\eta\left(y,w_f\right)\right]dy \tag{30}$$

Differentiating (30) with respect to $w_f$we have that:

$$\frac{\partial logn\left(w_f;\mathcal{F}\cup\{j\}\right)}{\partial w_f}=\frac{\partial logn\left(w_f;\mathcal{F}\right)}{\partial w_f}+\frac{\int_0^1 G'\left(\right)\left[\beta+\frac{\partial\eta\left(y,w_f\right)}{\partial w_f}\right]dy}{\int_0^1 G\left[\beta\left(w_f-w_j\right)+\eta\left(y,w_f\right)\right]dy} \tag{31}$$

Inspection of (31) shows the labor supply elasticity will be higher with the extra firm if the final term is positive for which a sufficient condition is that:

$$\left[\beta+\frac{\partial\eta\left(y,w_f\right)}{\partial w_f}\right]>0 \tag{32}$$

for all y. Taking logs of (28) and differentiating we have that:

$$0=\frac{\int_{\eta_{min}}^{\eta}g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta}g\left(x\right)Z\left(\beta w_f+x\right)dx}-\frac{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z\left(\beta w_f+x\right)dx}+\frac{g\left(\eta\right)Z\left(\beta w_f+\eta\right)}{\int_{\eta_{min}}^{\eta}g\left(x\right)Z\left(\beta w_f+x\right)dx}\frac{\partial\eta\left(y,w_f\right)}{\partial w_f} \tag{33}$$

The condition (32) can then be written as:

$$g\left(\eta\right)Z\left(\beta w_f+\eta\right)-\int_{\eta_{min}}^{\eta}g\left(x\right)Z'\left(\beta w_f+x\right)dx+\int_{\eta_{min}}^{\eta}g\left(x\right)Z\left(\beta w_f+x\right)dx\frac{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z\left(\beta w_f+x\right)dx}>0 \tag{34}$$

Integrating the second term by parts this condition can be written as:

$$\int_{\eta_{min}}^{\eta}g'\left(x\right)Z\left(\beta w_f+x\right)dx+\int_{\eta_{min}}^{\eta}g\left(x\right)Z\left(\beta w_f+x\right)dx\frac{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z\left(\beta w_f+x\right)dx}>0 \tag{35}$$

Integrating the numerator of the final term by parts and dividing by the first part of the final term, this can be written as:

$$\frac{\int_{\eta_{min}}^{\eta}\frac{g'(x)}{g(x)}g\left(x\right)Z\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta}g\left(x\right)Z\left(\beta w_f+x\right)dx}-\frac{\int_{\eta_{min}}^{\eta_{max}}\frac{g'(x)}{g(x)}g\left(x\right)Z'\left(\beta w_f+x\right)dx}{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z\left(\beta w_f+x\right)dx}+\frac{g\left(\eta_{max}\right)Z'\left(\beta w_f+\eta_{max}\right)}{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z\left(\beta w_f+x\right)dx}>0 \tag{36}$$

This can be written as:

$$E\left[\frac{g'\left(x\right)}{g\left(x\right)}|x\leq\eta\right]-E\left[\frac{g'\left(x\right)}{g\left(x\right)}|x\leq\eta_{max}\right]+\frac{g\left(\eta_{max}\right)Z'\left(\beta w_f+\eta_{max}\right)}{\int_{\eta_{min}}^{\eta_{max}}g\left(x\right)Z\left(\beta w_f+x\right)dx}>0 \tag{37}$$

From log concavity of g, $\frac{g'(x)}{g(x)}$ is decreasing in x so that the first term is bigger than the second term. As the final term is also positive this proves the Proposition.

8.2 Proof of Proposition 2

8.2.1 Proof of Proposition 2.1

Consider the case where there are C firms all but one paying the same wage w and employment is always preferred to unemployment. We will consider a single firm that possibly deviates by pying a wage w_f (though it won't in equilibrium). Labor supply 14 then becomes:

$$n(w_f;C) = \int_{\eta_{min}}^{\eta_{max}} g(\eta)\, G(\beta(w_f - w) + \eta)^{C-1}\, d\eta \tag{38}$$

and the elasticity of labor supply can be written as:

$$\epsilon = (C-1)\frac{\int_{\eta_{min}}^{\eta_{max}} g(\eta)\, g(\beta(w_f - w) + \eta)\, G(\beta(w_f - w) + \eta)^{C-2}\, d\eta}{\int_{\eta_{min}}^{\eta_{max}} g(\eta)\, G(\beta(w_f - w) + \eta)^{C-1}\, d\eta} \tag{39}$$

Evaluating at a symmetric equilibrium $w_f = w$ we have that:

$$\epsilon = C(C-1)\int_{\eta_{min}}^{\eta_{max}} g(\eta)^2\, G(\eta)^{C-2}\, d\eta \tag{40}$$

as the numerator of (39) will be $1/C$. Integrating by parts we have that:

$$\epsilon = C\left[g(\eta)\, G(\eta)^{C-1}\right]_{\eta_{min}}^{\eta_{max}} - C\int_{\eta_{min}}^{\eta_{max}} g'(\eta)\, G(\eta)^{C-1}\, d\eta = Cg(\eta_{max}) - C\int_{\eta_{min}}^{\eta_{max}} \frac{g'(\eta)}{g(\eta)} g(\eta)\, G(\eta)^{C-1}\, d\eta \tag{41}$$

and integrating the final term by parts leads to:

$$\epsilon = Cg(\eta_{max}) - \left[\frac{g'(\eta)}{g(\eta)} G(\eta)^C\right]_{\eta_{min}}^{\eta_{max}} + \int_{\eta_{min}}^{\eta_{max}} \left[\frac{g'(\eta)}{g(\eta)}\right]' G(\eta)^C\, d\eta \tag{42}$$

which becomes (5).

8.2.2 Proof of Proposition 2.2

Differentiating (5) with respect to C leads to:

$$\frac{\partial \epsilon}{\partial C} = g(\eta_{max}) + \int_{\eta_{min}}^{\eta_{max}} \left[\frac{g'(\eta)}{g(\eta)}\right]' [logG(\eta)]\, G(\eta)^C\, d\eta \tag{43}$$

The first term is obviously non-negative positive. The second term is also positive because log concavity of $g(\eta)$ implies that $\left[\frac{g'(\eta)}{g(\eta)}\right]' \leq 0$ and $logG(\eta) \leq 0$. Now differentiate again to give:

$$\frac{\partial^2 \epsilon}{\partial C^2} = \int_{\eta_{min}}^{\eta_{max}} \left[\frac{g'(\eta)}{g(\eta)}\right]' [logG(\eta)]^2\, G(\eta)^C\, d\eta \tag{44}$$

This must be non-positive proving concavity.

8.2.3 Proof of Proposition 2.3

Because $G(\eta) \leq 1$ the final two terms in (5) must be less than or equal to $\left[\frac{g'(\eta_{min})}{g(\eta_{min})}\right]$ for all C. So the limit of these terms must be finite. The limit of the elasticity is then finite if $g(\eta_{max}) = 0$, infinite if $g(\eta_{max}) > 0$.

8.3 Proof of Proposition 3

8.3.1 Proof of Proposition 3.1

An increase in $\frac{\lambda}{\delta}$leads to a shift in the distribution of x in the sense of first-order stochastic dominance. This causes weighted average to shift towards the case where more opportunities which by Proposition 1.3 leads to lower market power

8.3.2 Proof of Proposition 3.2

An increase in C leads to an increase in the number of opportunities for a given x in the sense of first-order stochastic dominance. By Proposition 1.3 this leads to lower market power for every x

8.4 The distribution of x

The rate at which workers move from having had 0 opportunities to having 1 offer is λ so total outflows from the state are $\lambda\phi(0)$; the inflows into this state are $\delta(1-\phi(0))$. Equating inflows and outflows gives us:

$$\phi(0) = \frac{\delta}{\delta + \lambda} \tag{45}$$

The rate at which workers move from having had $x-1$ opportunities to having x offers is λ. The rate at which workers exit having had x opportunities is δ to unemployment and λ to having $(x+1)$. Hence the fraction of workers having had x opportunities, $\phi(x)$ follows the recursion:

$$\phi(x) = \frac{\lambda}{\delta + \lambda}\phi(x-1) \tag{46}$$

Combining (45) and (46) leads to (6)

Appendix B

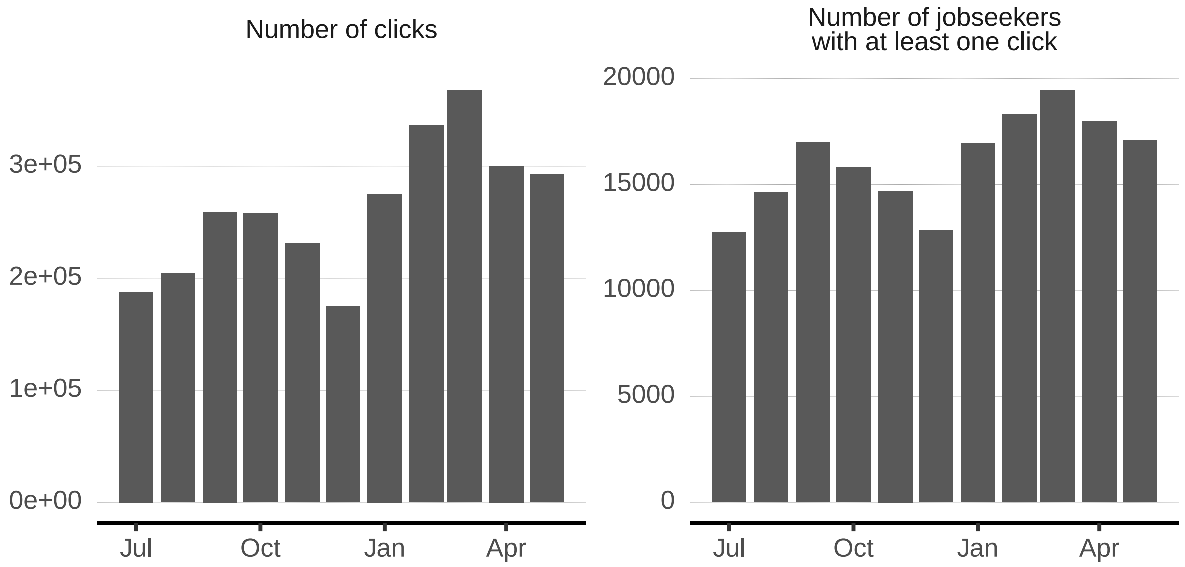

Figure 20: Usage of the job room over time by the registered jobseekers in our sample.

Measurement	Mean	SD	Min	p25	p50	p75	Max
c	15.83	49.84	1.00	4.00	8.00	15.00	1647.00
c corrected	1.41	2.39	1.00	1.03	1.09	1.25	81.82
total clicks	243.74	373.30	1.00	57.00	132.00	277.00	4524.00
total c lambda corrected	1234.17	1528.14	56.59	463.77	782.79	1406.58	18444.48
total clicks c corrected	6.62	15.08	1.00	1.83	3.12	6.11	281.91
total clicks both corrected	36.22	62.47	4.82	15.52	22.35	35.46	1149.35
n overlap	98.48	177.04	1.00	25.00	53.00	108.00	3761.00
overlap lambda cor	516.98	747.75	4.08	204.86	331.42	559.96	15333.71
overlap c corrected	3.63	8.67	0.96	1.35	1.89	3.18	237.94
overlap both cor	21.85	37.51	4.07	10.02	14.14	21.66	970.09
c new firms	8.42	13.89	1.00	3.00	5.00	10.00	373.00
c new ads	14.75	47.59	1.00	4.00	7.00	14.00	1463.00

Table 4: The input quantities for the different HHI measures. Summary statistics over jobseeker-ad pairs.

Measurement	Mean	SD	Min	p25	p50	p75	Max
share by session	0.21	0.24	0	0.06	0.13	0.25	1
share by spell	0.02	0.06	0	0.00	0.01	0.02	1

Table 5: The input quantities for the HHI measures taking into account vacancy heterogeneity. Summary statistics over jobseeker-ad pairs.

	c	c$_c$orrected	c$_n$ew$_a$ds	c$_n$ew$_f$irms	cell$_h$hi	n$_o$verlap	overlap$_b$oth$_c$or	overlap$_{cc}$orrected	overlap$_l$ambda$_c$or	share$_b$y$_s$ession	share$_b$y$_s$pell	total$_{cl}$ambda$_c$orrected	total$_c$licks	total$_c$licks$_b$oth$_c$orrected	total$_c$licks$_{cc}$orrected
c	1.0000000	0.3962209	0.8446572	0.6233904	0.1049256	0.3709409	-0.0204971	0.2990127	0.1966868	0.9911883	0.2885233	0.2935953	0.2886810	-0.0085087	0.2768739
c$_c$orrected	0.3962209	1.0000000	0.3912999	0.3405977	-0.0431618	0.1805303	0.4764393	0.6088681	0.1551796	0.3968279	0.1427013	0.1291342	0.1412504	0.4626901	0.4500591
c$_n$ew$_a$ds	0.8446572	0.3912999	1.0000000	0.7092216	0.0905171	0.3567219	-0.0027123	0.2862248	0.1844281	0.8365350	0.2775357	0.2665945	0.2779119	0.0052429	0.2602087
c$_n$ew$_f$irms	0.6233904	0.3405977	0.7092216	1.0000000	0.0787694	0.3287478	0.0034266	0.2342590	0.1582531	0.6166682	0.2598328	0.2239519	0.2609213	0.0011972	0.2100090
cell$_h$hi	0.1049256	-0.0431618	0.0905171	0.0787694	1.0000000	0.0924386	-0.1566834	-0.0010186	0.0378743	0.1039785	0.0702378	0.1027823	0.0729293	-0.1435600	0.0332579
n$_o$verlap	0.3709409	0.1805303	0.3567219	0.3287478	0.0924386	1.0000000	-0.0057058	0.3954748	0.4155483	0.3683113	0.7944228	0.5495763	0.8033503	-0.0481865	0.4331717
overlap$_b$oth$_c$or	-0.0204971	0.4764393	-0.0027123	0.0034266	-0.1566834	-0.0057058	1.0000000	0.5013842	0.2333442	-0.0209795	-0.0387055	-0.0899655	-0.0385823	0.6744190	0.1401565
overlap$_{cc}$orrected	0.2990127	0.6088681	0.2862248	0.2342590	-0.0010186	0.3954748	0.5013842	1.0000000	0.3407823	0.2981551	0.3061225	0.4008792	0.3042077	0.3993632	0.8202401
overlap$_l$ambda$_c$or	0.1966868	0.1551796	0.1844281	0.1582531	0.0378743	0.4155483	0.2333442	0.3407823	1.0000000	0.1953800	0.1070545	0.1518219	0.1070785	0.0153698	0.1553242
share$_b$y$_s$ession	0.9911883	0.3968279	0.8365350	0.6166682	0.1039785	0.3683113	-0.0209795	0.2981551	0.1953800	1.0000000	0.2899234	0.2922555	0.2864757	-0.0078826	0.2765971
share$_b$y$_s$pell	0.2885233	0.1427013	0.2775357	0.2598328	0.0702378	0.7944228	-0.0387055	0.3061225	0.1070545	0.2899234	1.0000000	0.6402016	0.9862952	-0.0236105	0.4219842
total$_{cl}$ambda$_c$orrected	0.2935953	0.1291342	0.2665945	0.2239519	0.1027823	0.5495763	-0.0899655	0.4008792	0.1518219	0.2922555	0.6402016	1.0000000	0.6454138	0.0928505	0.5997694
total$_c$licks	0.2886810	0.1412504	0.2779119	0.2609213	0.0729293	0.8033503	-0.0385823	0.3042077	0.1070785	0.2864757	0.9862952	0.6454138	1.0000000	-0.0249142	0.4205639
total$_c$licks$_b$oth$_c$orrected	-0.0085087	0.4626901	0.0052429	0.0011972	-0.1435600	-0.0481865	0.6744190	0.3993632	0.0153698	-0.0078826	-0.0236105	0.0928505	-0.0249142	1.0000000	0.3545894
total$_c$licks$_{cc}$orrected	0.2768739	0.4500591	0.2602087	0.2100090	0.0332579	0.4331717	0.1401565	0.8202401	0.1553242	0.2765971	0.4219842	0.5997694	0.4205639	0.3545894	1.0000000

Table 6: Correlations between the different concentration indices. Correlations over all vacancies with at least 10 clicks and a non-missing value of each index.

Appendix C: How Search Activity Varies Over a Spell of Unemployment

While Figures 5 and 6 show the number of sessions and clicks per session on average, there may be considerable heterogeneity. Figures 25 and 26 present some simple regressions on how the number of sessions and the number of clicks per session vary. We are particularly interested in how search intensity varies over the duration of the unemployment spell. The first specification shows how the two dimensions of search activity vary with duration when only controls for time-effects are included (by adding dummies for the four quarters for which we have data to the regression[14]). The duration dependence can be the result of true duration dependence or unobserved heterogeneity if (as is the case) those with greater search intensity have shorter

[14]The four quarters are 2020Q3, 2020Q4, 2021Q1, 2022Q2.

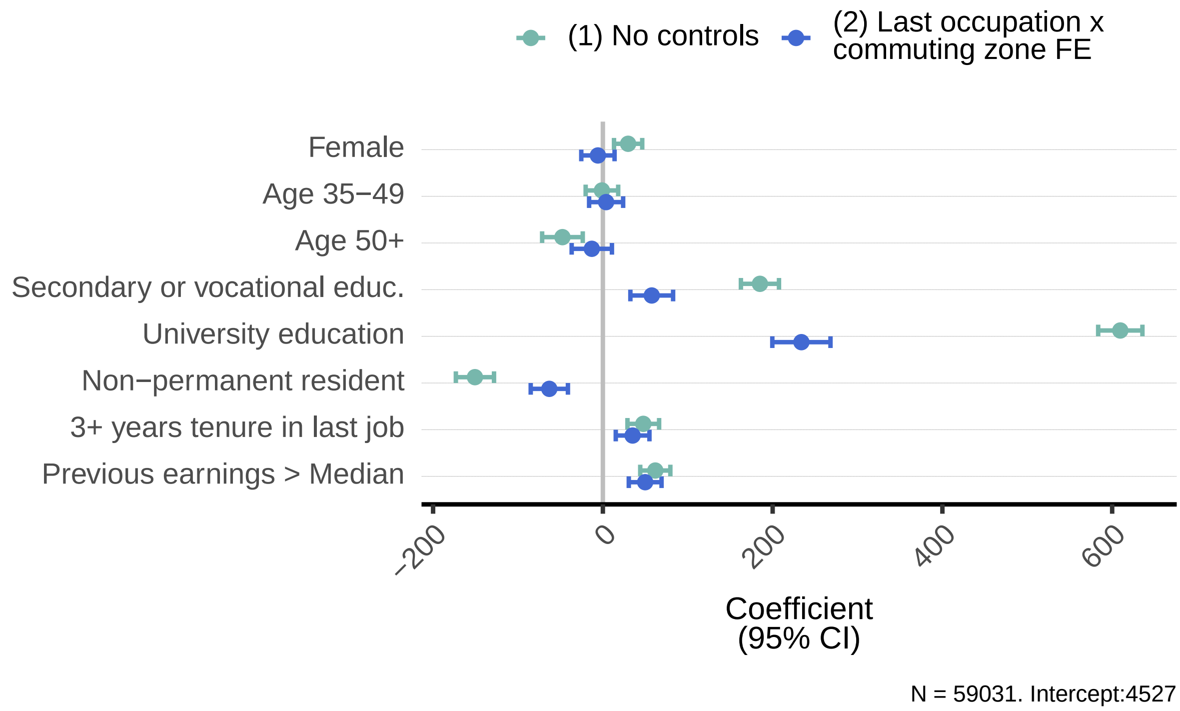

Figure 21: OLS regression of the jobseeker-level HHI on jobseeker characteristics. The jobseeker average HHI is computed as follows: $HHI_i = \sum_{f \in \mathcal{F}} \frac{s_{if}}{\sum s_{if}} HHI_f$. s_{ij} is the share of vacancy f in jobseekers i's portfolio, over the whole spell, where every session gets equal weights, e.g. if a jobseeker has 5 sessions and vacancy f gets clicked in one of the sessions together with 9 other vacancies, then $s_{if} = 1/50$. HHI_f is defined following equation 19, $HHI_f = \frac{\sum_i \left(\frac{1}{C_i}\right)^2}{\sum_i \left(\frac{1}{C_i}\right)}$

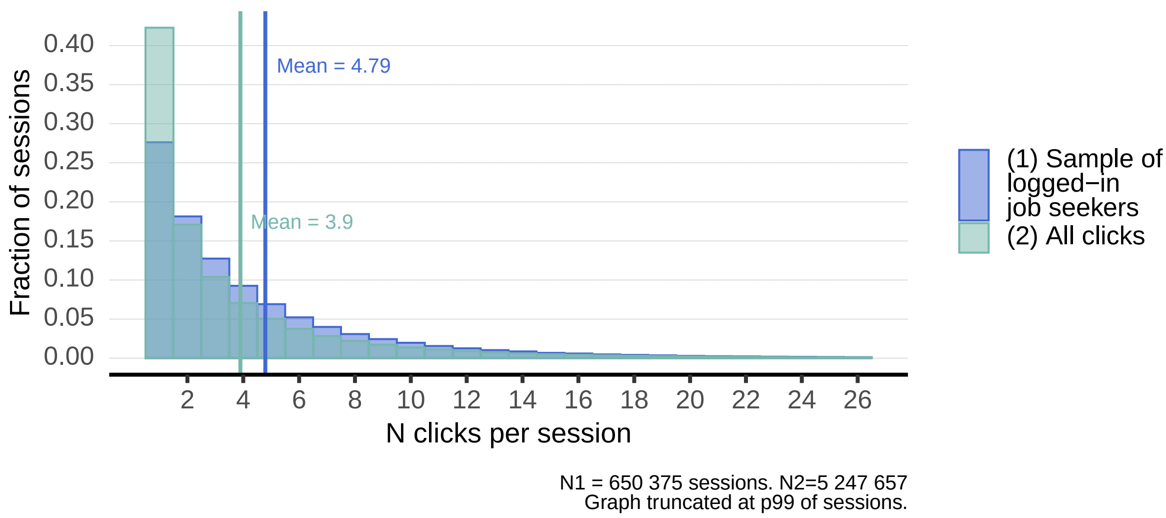

Figure 22: Distribution of number of clicks per session. Comparison between our sample of registered (and logged-in) jobseekers and all users of the platform. For the non logged-in users we define a search session by day (as in the other parts of the paper) and IP address. We exclude the IP addresses with a number of clicks higher than the 99.9 percentile (929 clicks)

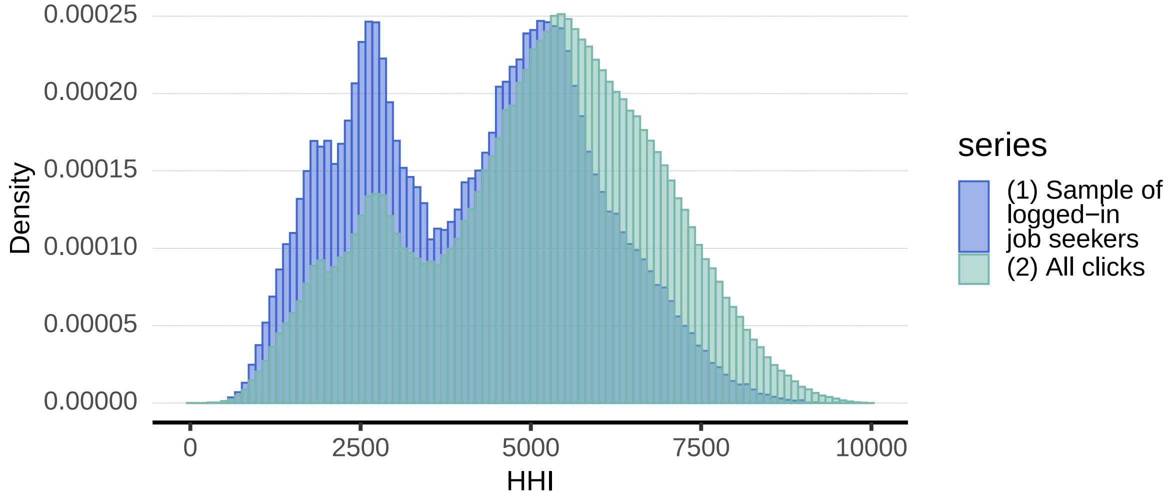

Figure 23: Distribution of the HHI calculated using the number of clicks per session as in Figure 7. Comparison between the HHI computed in our sample of registered (and logged-in) jobseekers and all users of the platform. For the non logged-in users we define a search session by day (as in the other parts of the paper) and IP address. We exclude the IP addresses with a number of clicks higher than the 99.9 percentile (929 clicks)

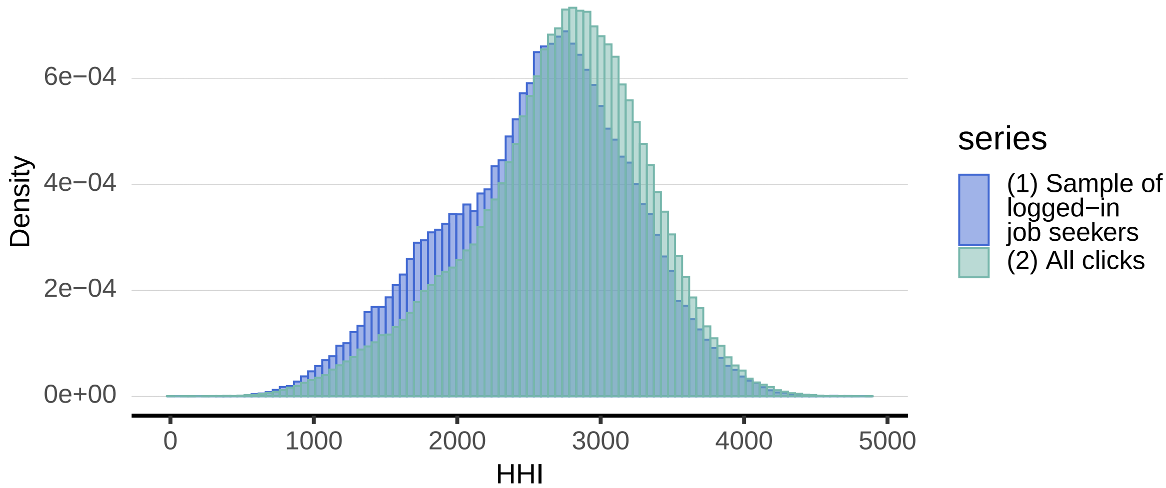

Figure 24: Distribution of the HHI calculated using the number of clicks per session as in Figure 7. This figure excludes sessions with 1 click only. Comparison between the HHI computed in our sample of registered (and logged-in) jobseekers and all users of the platform. For the non logged-in users we define a search session by day (as in the other parts of the paper) and IP address. We exclude the IP addresses with a number of clicks higher than the 99.9 percentile (929 clicks)

durations. The second specification shows how results change when we control for the individual characteristics of the unemployed and the final specification when we control for individual fixed effects.

Figure 25 shows that, on average, a jobseeker has 2.13 sessions in the first month of spell and this number declines by around 10% in the second month and goes down to a constant level 40% below the initial level after around 8 months. This pattern also holds conditional

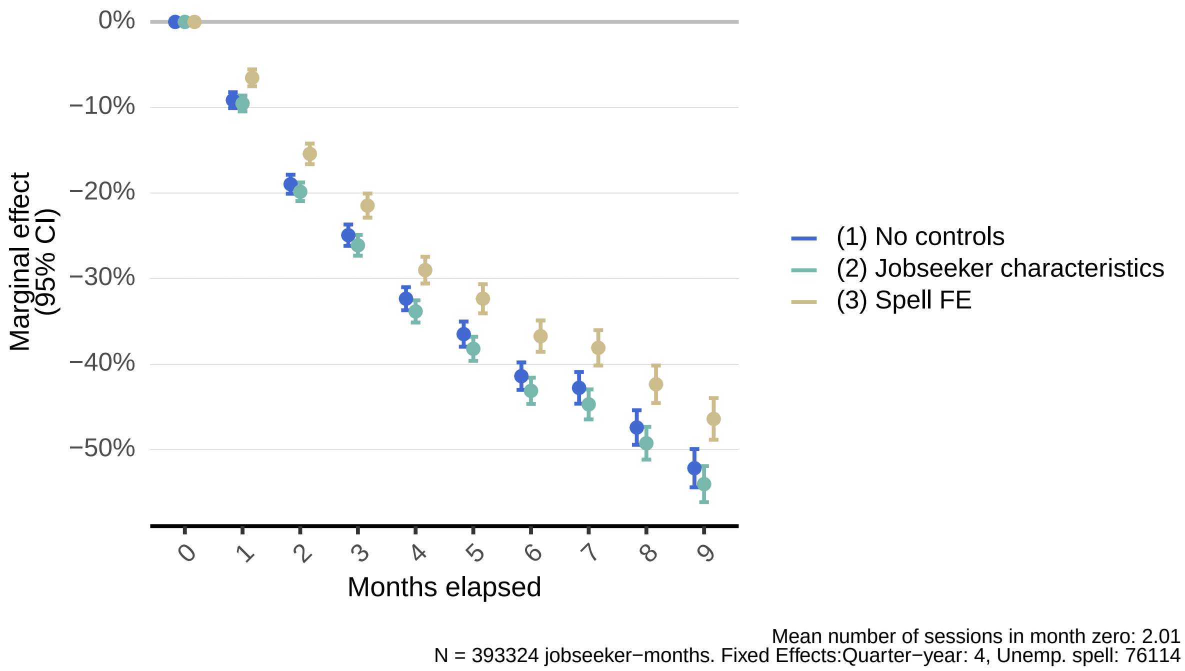

Figure 25: Poisson regressions of the number of session per elapsed month of unemployment spell. Marginal effects are shown. The regressions exclude jobseekers with an unemployment spell shorter than 60 days.

on last occupation, commuting zone, age, education, residence permit, insured earnings and tenure at the last job prior to unemployment. Once we control for unobserved heterogeneity (specification (3)), the decline is less steep. Figure 26 shows that, conditional on having at least one session, the average number of clicks in the first month of the unemployment spell is 4.83. The number declines by around 8% to around 4.6 clicks in the subsequent months. Once we control for unobserved heterogeneity, the number of clicks per session declines steadily over the search spell. This difference suggests that actually, jobseekers with longer spell durations tend to click on more vacancy postings per session. Appendix B Figure **??** looks at the number of clicks not over spell duration but over the order of sessions and shows very similar patterns.

Figure 27 shows the product of the clicks per session and the number of sessions; the cumulative number of clicks over the spell.

We also present some results where the outcome is the number of new clicks defined as the particular vacancy or the particular firm. Figure 28 shows how those two outcomes compare to all new clicks. The regressions are conditional on jobseeker-spell fixed effects, as in specification (3) above. Comparing spcification (1) and (2) of Figure 28 suggests that most new clicks are on vacancy postings that haven't been clicked on before and excluding the clicks on previously seen vacancies doesn't significantly change the path of clicks over time. However, specification (3) shows that the decline is sharper when we only consider clicks on firms that haven't been considered before. The slope of the decrease is around twice as steep as for the baseline specification. Overall, the results indicate that opportunities become more limited.

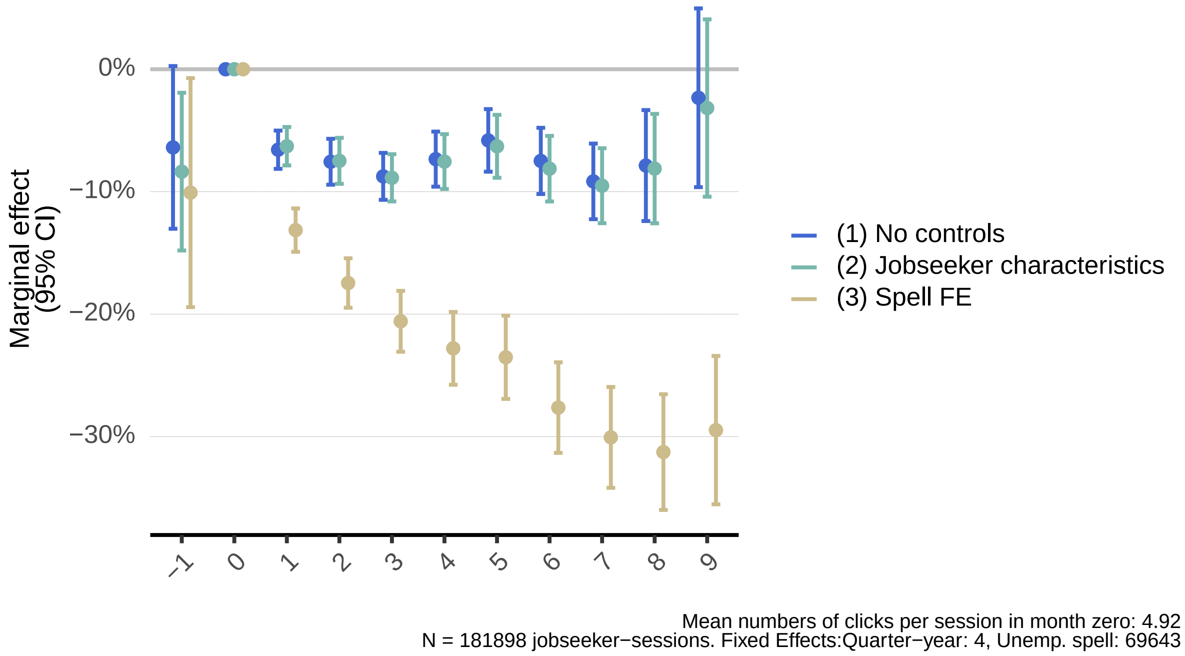

Figure 26: Poisson regressions of the average clicks per session on the elapsed month of unemployment spell. The regressions are conditional on having at least one session in a month. Marginal effects are shown. The regressions exclude jobseekers with an unemployment spell shorter than 60 days.

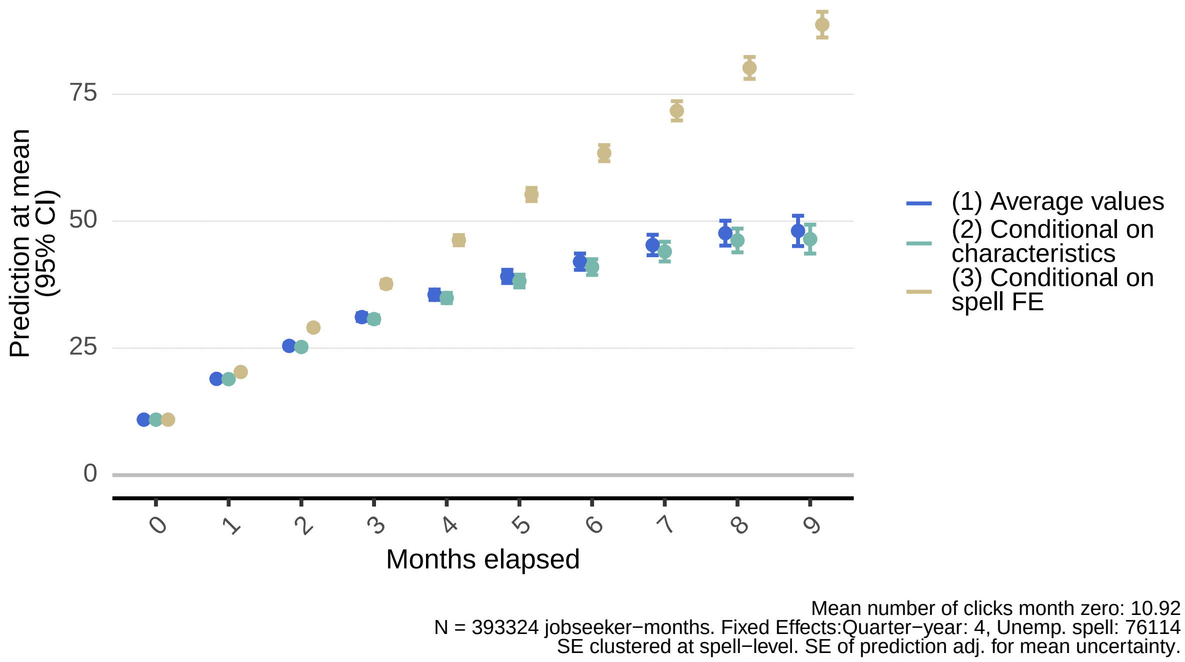

Figure 27: Predicted number of total clicks accumulated over the spell by jobseeker. Prediction from a Poisson regressions of the cumulated number of clicks on the elapsed month of unemployment spell. The regressions exclude jobseekers with an unemployment spell shorter than 60 days.

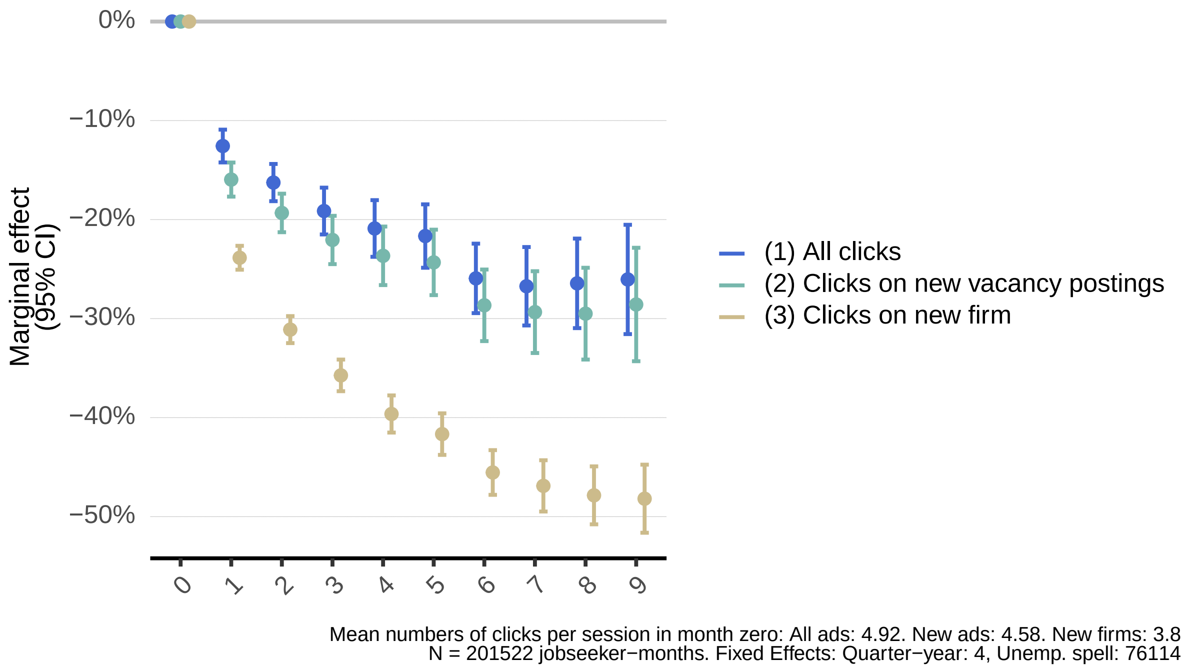

Figure 28: Poisson regressions of the average clicks per session on the elapsed month of unemployment spell. The regressions are conditional on having at least one session in a month. All regressions include jobseeker-spell fixed effects. Marginal effects are shown. The regressions exclude jobseekers with an unemployment spell shorter than 60 days.